Bike Sharing - Hypothesis Testing

May 21, 2024

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import ttest_ind, chi2_contingency, f_oneway, levene
from statsmodels.graphics.gofplots import qqplot
```

---

1 Objective :

A bike sharing company has recently faced a significant dip in its revenue and we would like to understand why. Especially as data scientists, determine the factors which are good predictors of demand with a certain level of confidence. Further on the basis of these strong predictors of demand we also need to give recommendations to the company.

2 Insights :

- Clear, working winter day is the most common day reported in the data
- The count of casual, registered and total rental bikes per hour shows a somewhat poisson distribution
- Temp, feeling temp, humidity and windspeed are also somewhat normally distributed centered around 20, 25, 60 and 13 respectively
- Insights from visual EDA :
  - Most bikes seems to be rented in fall and the least in spring
  - There seems to be slightly more number of bikes rented on a holiday as compared to no holiday (very small difference)
  - There seems to be slightly lesser number of bikes rented on a working day (very small difference)
  - Most bikes are rented on clear days and the least on rainy days
- We cannot infer that working day has an effect on number of bikes rented (t-test pvalue is 22.6%)

- We can infer that weather has a significant effect on number of bikes rented (f-test pvalue is ~0%)
- We can infer that clear weather is linked to increase in number of bikes rented (Welch t-test pvalue ~0%)
- We can infer that season has a significant effect on number of bikes rented (f-test pvalue is ~0%)
- We can infer that summer and fall season is linked to increase in number of bikes rented (Welch t-test pvalue ~0%)
- We can infer that season has a significant effect on the weather (chisquare-test pvalue is ~0%)

3 Recommendations :

- The bike sharing company should start extensive marketing campaigns at the start of summer season and run them all the way through fall season.
- During these 2 seasons they should increase their supply of cycles, and install more pick up/drop locations to make sure that the demand is fully met.
- They should also introduce Miles Points (like flights) during these seasons to build customer loyalty and retain them for the next year as well.

4 EDA

4.1 Non Visual

[2]:
```
df = pd.read_csv('bike_sharing.csv')
```

[3]:
```
df.shape
```

[3]:
```
(10886, 12)
```

[4]:
```
df.head()
```

[4]:
```
              datetime  season  holiday  workingday  weather  temp   atemp  \
0  2011-01-01 00:00:00       1        0           0        1  9.84  14.395
1  2011-01-01 01:00:00       1        0           0        1  9.02  13.635
2  2011-01-01 02:00:00       1        0           0        1  9.02  13.635
3  2011-01-01 03:00:00       1        0           0        1  9.84  14.395
4  2011-01-01 04:00:00       1        0           0        1  9.84  14.395

   humidity  windspeed  casual  registered  count
0        81        0.0       3          13     16
1        80        0.0       8          32     40
2        80        0.0       5          27     32
```

```
3         75         0.0         3            10       13
4         75         0.0         0             1        1
```

[5]:
```
df.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
```

- No nulls found in data

[6]:
```
#Changing dtype:
df['datetime'] = pd.to_datetime(df['datetime'], format='%Y-%m-%d %H:%M:%S')

#Coverting to categorical values for easier interpretation of data
df['season'] = df['season'].replace({1:'spring',2:'summer',3:'fall',4:'winter'})
df['holiday'] = df['holiday'].replace({1:'holiday',0:'no holiday'})
df['workingday'] = df['workingday'].replace({1:'workingday',0:'no workingday'})
df['weather'] = df['weather'].replace({1:'clear',2:'mist',3:'light rain/snow',4:
 ↪'heavy rain/snow'})
```

[7]:
```
df.describe(datetime_is_numeric=True)
```

[7]:

	datetime	temp	atemp	humidity
count	10886	10886.00000	10886.000000	10886.000000
mean	2011-12-27 05:56:22.399411968	20.23086	23.655084	61.886460
min	2011-01-01 00:00:00	0.82000	0.760000	0.000000
25%	2011-07-02 07:15:00	13.94000	16.665000	47.000000
50%	2012-01-01 20:30:00	20.50000	24.240000	62.000000
75%	2012-07-01 12:45:00	26.24000	31.060000	77.000000
max	2012-12-19 23:00:00	41.00000	45.455000	100.000000
std	NaN	7.79159	8.474601	19.245033

\

```
        windspeed        casual    registered         count
count  10886.000000  10886.000000  10886.000000  10886.000000
mean      12.799395     36.021955    155.552177    191.574132
min        0.000000      0.000000      0.000000      1.000000
25%        7.001500      4.000000     36.000000     42.000000
50%       12.998000     17.000000    118.000000    145.000000
75%       16.997900     49.000000    222.000000    284.000000
max       56.996900    367.000000    886.000000    977.000000
std        8.164537     49.960477    151.039033    181.144454
```

[8]:
```
df.describe(include='O')
```

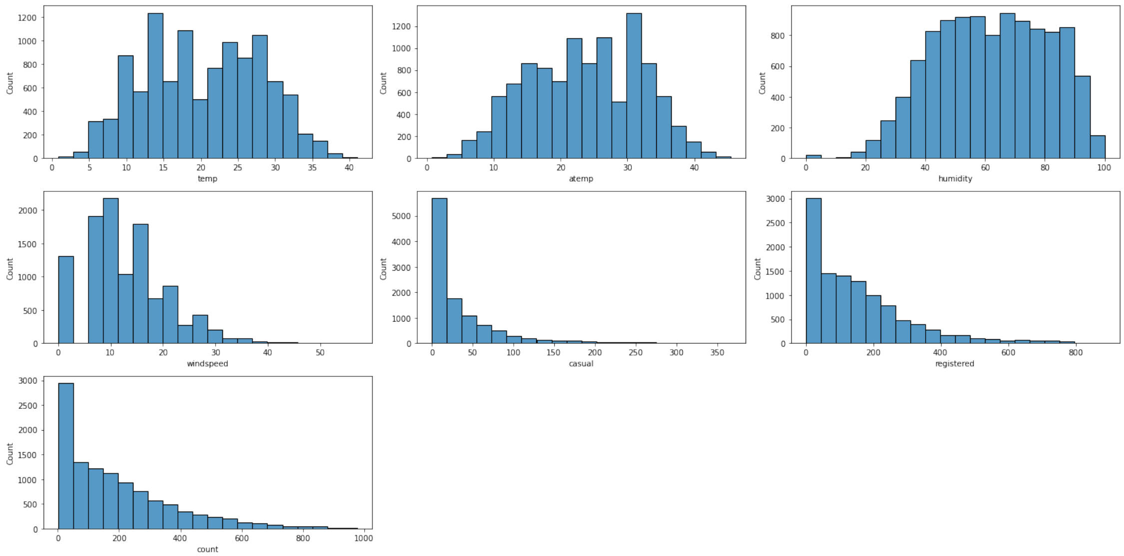
[8]:
```
        season     holiday  workingday weather
count    10886       10886       10886   10886
unique       4           2           2       4
top     winter  no holiday  workingday   clear
freq      2734       10575        7412    7192
```

- Clear, working winter day is the most common day reported in the data

4.2 Visual EDA

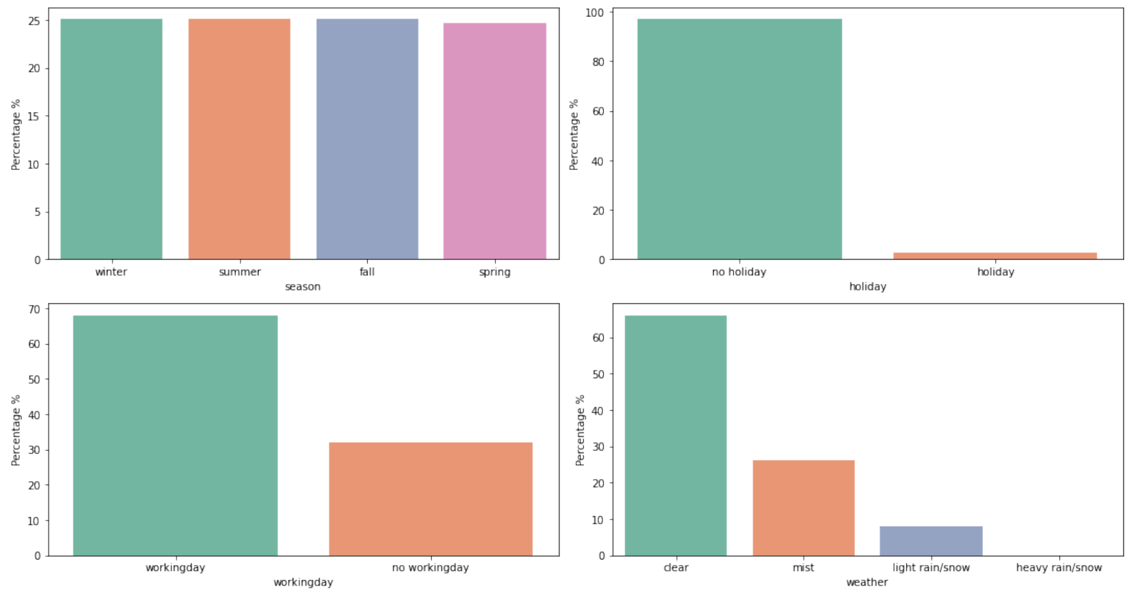
4.2.1 Univariate

[10]:
```
plt.rcParams['figure.figsize'] = (20,10)
plt.rcParams['figure.autolayout'] = True
continous_variables = ['temp', 'atemp', 'humidity', 'windspeed',␣
↪'casual','registered', 'count']
for e, c in enumerate(continous_variables):
    ax = plt.subplot(3,3,e+1)
    sns.histplot(df[c],ax=ax, bins=20)
```



- The count of casual, registered and total rental bikes per hour shows a somewhat poisson distribution
- Temp, feeling temp, humidity and windspeed are also somewhat normally distributed centered around 20, 25, 60 and 13 respectively

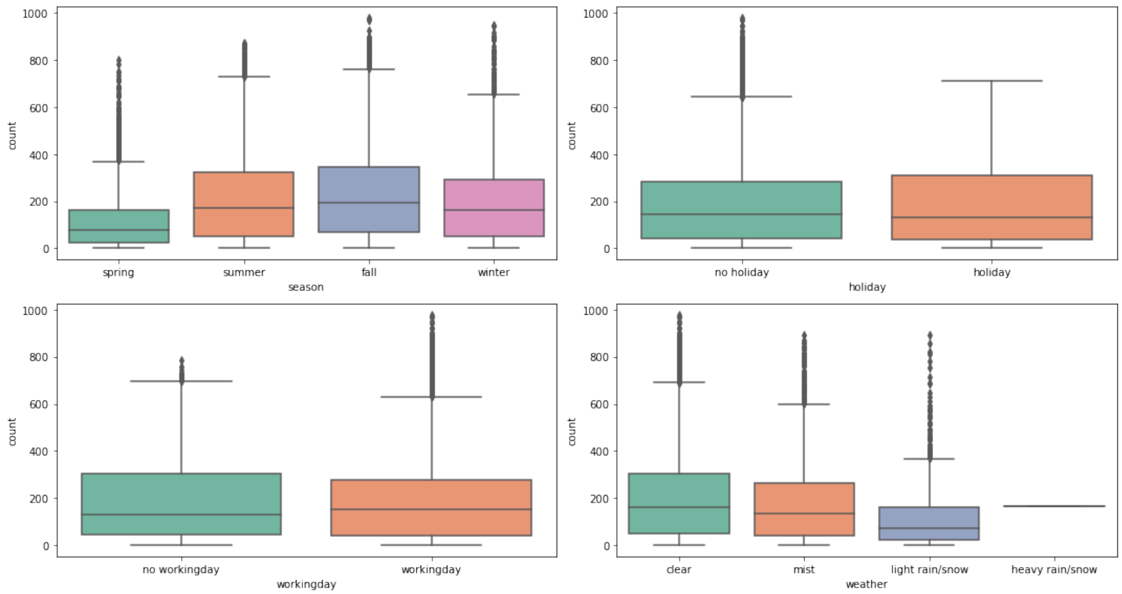
[11]:
```python
plt.rcParams['figure.figsize'] = (15,8)
categorical_variables = ['season','holiday','workingday','weather']
for e,c in enumerate(categorical_variables):
    ax = plt.subplot(2,2,e+1)
    data = df[c].value_counts(1) * 100
    sns.barplot(x=data.index, y=data.values, ax=ax, palette='Set2')
    ax.set_ylabel('Percentage %')
    ax.set_xlabel(c)
```



- We have equal data for all the 4 seasons
- We have less than 10% data from holidays (Because there are very few holidays in a year)
- Around 65% of the days are working in a year (Based on holidays + weekends)
- Around 65% of the days had clear weather, and almost 0% days had heavy rain

4.2.2 Bivariate

[12]:
```
fig,ax = plt.subplots(2,2,figsize=(15,8))
sns.boxplot(x='season', y='count', data=df, ax=ax[0][0], palette='Set2')
sns.boxplot(x='holiday', y='count', data=df, ax=ax[0][1], palette='Set2')
sns.boxplot(x='workingday', y='count', data=df, ax=ax[1][0], palette='Set2')
sns.boxplot(x='weather', y='count', data=df, ax=ax[1][1], palette='Set2')
print()
```



- From the above boxplots we can say :
  - Most bikes seems to be rented in fall and the least in spring
  - There seems to be slightly more number of bikes rented on a holiday as compared to no holiday (very small difference)
  - There seems to be slightly lesser number of bikes rented on a working day (very small difference)
  - Most bikes are rented on clear days and the least on rainy days

5 Hypothesis Testing

[13]:
```
df_copy = pd.read_csv('bike_sharing.csv')
```

5.1 Does Working Day effects bike rentals?

- H0 : Working day has no effect on number of bikes rented
- Ha : Working day has an effect on number of bikes rented
- Significance level : 5%
- Test Statistic : t-test score (2 Sample t-test)

[14]:
```
bikes_on_working_day = df_copy.loc[df_copy['workingday'] == 1,'count'].values
bikes_on_non_working_day = df_copy.loc[df_copy['workingday'] == 0,'count'].
 ↪values
```

5.1.1 Checking ttest assumptions

[15]:
```
# Equal Variance : Both samples need to have equal variance otherwise we will␣
↪do a Welch t-test
# Null hypothesis : There is no difference of standard deviation between the␣
↪samples
# Alternate hypothesis : There is a difference of standard deviation between␣
↪the samples
# We can do a levene test to check this at a significance level of 5%

levene(bikes_on_working_day, bikes_on_non_working_day)
```

[15]:
```
LeveneResult(statistic=0.004972848886504472, pvalue=0.9437823280916695)
```

- The levene test gives a pvalue of 94% which is much higher than our significance level
- Hence we cannot reject the null hypothesis
- Hence we cannot say that these distributions have different standard deviations

[16]:
```
# We will do a 2 sample t-test to check if these two are independent or not
ttest_ind(bikes_on_working_day, bikes_on_non_working_day)
```

[16]:
```
Ttest_indResult(statistic=1.2096277376026694, pvalue=0.22644804226361348)
```

- We get a t-test score of 1.2
- Our pvalue is 22.6% which is much higher than our significance level of 5%
- We cannot reject the H0
- We cannot infer that working day has an effect on number of bikes rented

---

5.2 Does Weather effects bike rentals?

[17]:
```
df_copy['weather'].value_counts()
```

[17]:
```
1    7192
2    2834
3     859
4       1
Name: weather, dtype: int64
```

- There is only 1 data point for weather type 4 ie (Heavy Rain + Ice Pallets + Thunderstorm + Mist, Snow + Fog)
- We will do ANOVA on the rest 3 weather types only

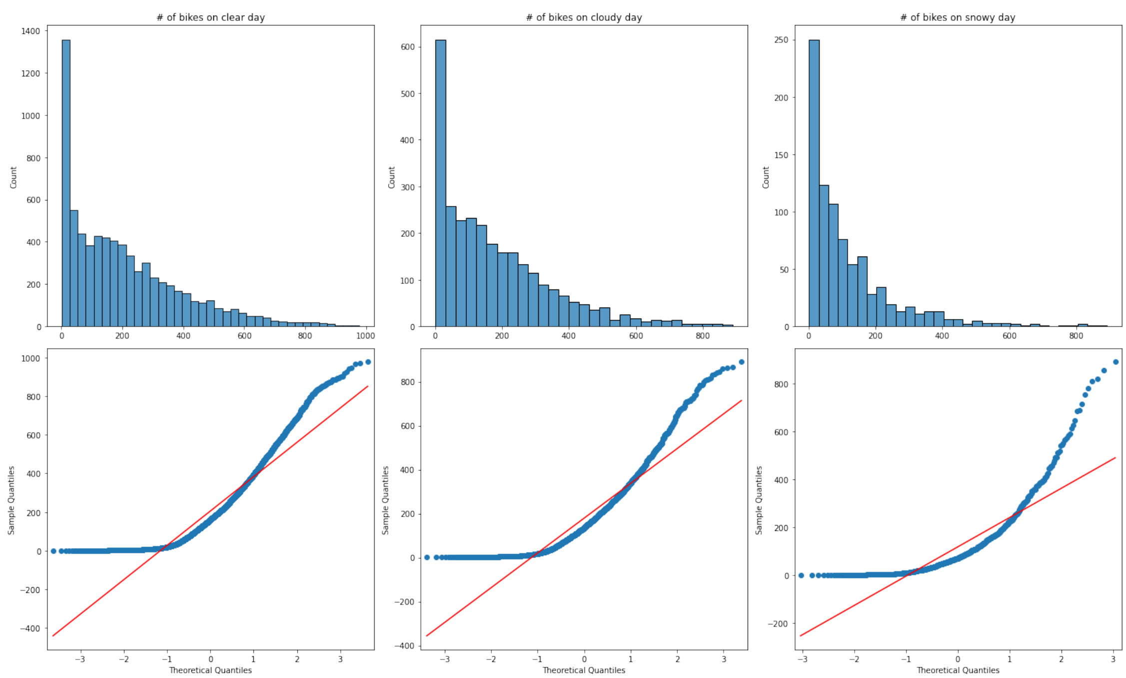
- H0 : Weather has no effect on number of bikes rented
- Ha : Weather has an effect on number of bikes rented
- Significance level : 5%
- Test Statistic : f-statistic (ANOVA)

[18]:
```
bikes_on_weather_type_1 = df_copy.loc[df_copy['weather'] == 1,'count'].values
bikes_on_weather_type_2 = df_copy.loc[df_copy['weather'] == 2,'count'].values
bikes_on_weather_type_3 = df_copy.loc[df_copy['weather'] == 3,'count'].values
```

5.2.1 Checking ANOVA assumptions

[19]:
```
# Normal Assumption : The sample distributions should be normally distributed
fig,ax = plt.subplots(2,3,figsize=(20,12))
sns.histplot(bikes_on_weather_type_1,ax=ax[0][0])
sns.histplot(bikes_on_weather_type_2,ax=ax[0][1])
sns.histplot(bikes_on_weather_type_3,ax=ax[0][2])
ax[0][0].set_title('# of bikes on clear day')
ax[0][1].set_title('# of bikes on cloudy day')
ax[0][2].set_title('# of bikes on snowy day')

qqplot(bikes_on_weather_type_1,line='r',ax=ax[1][0])
qqplot(bikes_on_weather_type_2,line='r',ax=ax[1][1])
qqplot(bikes_on_weather_type_3,line='r',ax=ax[1][2])
plt.show()
```



- We can see from above graphs that none of the distributions are normal

[20]:
```
# Equal Variance Assumption : The sample distribution should have equal variance
```

```
# Null hypothesis : There is no difference of standard deviation between the␣
↪samples
# Alternate hypothesis : There is a difference of standard deviation between␣
↪the samples
# We can do a levene test to check this at a significance level of 5%

levene(bikes_on_weather_type_1, bikes_on_weather_type_2,␣
↪bikes_on_weather_type_3)
```

[20]: LeveneResult(statistic=81.67574924435011, pvalue=6.198278710731511e-36)

- The levene test gives a pvalue of ~0% which is much less than our significance level
- Hence we can reject the null hypothesis
- Hence we can say that these distributions have different standard deviations

[21]:
```
# We now do a one way ANOVA to check the difference of means between the samples
f_oneway(bikes_on_weather_type_1, bikes_on_weather_type_2,␣
↪bikes_on_weather_type_3)
```

[21]: F_onewayResult(statistic=98.28356881946706, pvalue=4.976448509904196e-43)

- We get a fstat of 98.3
- Our pvalue is ~0% which is much lower than our significance level of 5%
- We reject the H0
- We can infer that weather has a significant effect on number of bikes rented

5.3 Are there more bikes rented on clear days?

- H0 : Clear weather has no effect on number of bikes rented
- Ha : Clear weather increases the number of bikes rented
- Significance level : 5%
- Test Statistic : t-test score (2 sample t-test)

[22]:
```
bikes_on_weather_type_2_and_3 = np.concatenate((bikes_on_weather_type_2,␣
↪bikes_on_weather_type_3))
```

[23]:
```
# Checking ttest assumptions
# Equal Variance Assumption : The sample distribution should have equal variance
# Null hypothesis : There is no difference of standard deviation between the␣
↪samples
# Alternate hypothesis : There is a difference of standard deviation between␣
↪the samples
# We can do a levene test to check this at a significance level of 5%

levene(bikes_on_weather_type_1, bikes_on_weather_type_2_and_3)
```

[23]: LeveneResult(statistic=87.13479803756756, pvalue=1.210545470625517e-20)

- The levene test gives a pvalue of ~0% which is much less than our significance level
- Hence we can reject the null hypothesis
- Hence we can say that these distributions have different standard deviations
- Hence we will do a Welch t-test instead here

[24]:
```
# We will do a 2 sample Welch t-test to check if these two are independent or
↪not
ttest_ind(bikes_on_weather_type_1, bikes_on_weather_type_2_and_3,
↪alternative='greater', equal_var=False)
```

[24]:
```
Ttest_indResult(statistic=11.5340767638041, pvalue=7.540763883724984e-31)
```

- We get a t-test score of 11
- Our pvalue is ~0% which is much lower than our significance level of 5%
- We can reject the H0
- We can infer that clear weather is linked to increase in number of bikes rented

---

5.4 Does season effects bike rentals?

[25]:
```
df_copy['season'].value_counts()
```

[25]:
```
4    2734
2    2733
3    2733
1    2686
Name: season, dtype: int64
```

- H0 : Season has no effect on number of bikes rented
- Ha : Season has an effect on number of bikes rented
- Significance level : 5%
- Test Statistic : f-statistic (ANOVA)

[26]:
```
bikes_on_season_type_1 = df_copy.loc[df_copy['season'] == 1,'count'].values
bikes_on_season_type_2 = df_copy.loc[df_copy['season'] == 2,'count'].values
bikes_on_season_type_3 = df_copy.loc[df_copy['season'] == 3,'count'].values
bikes_on_season_type_4 = df_copy.loc[df_copy['season'] == 4,'count'].values
```

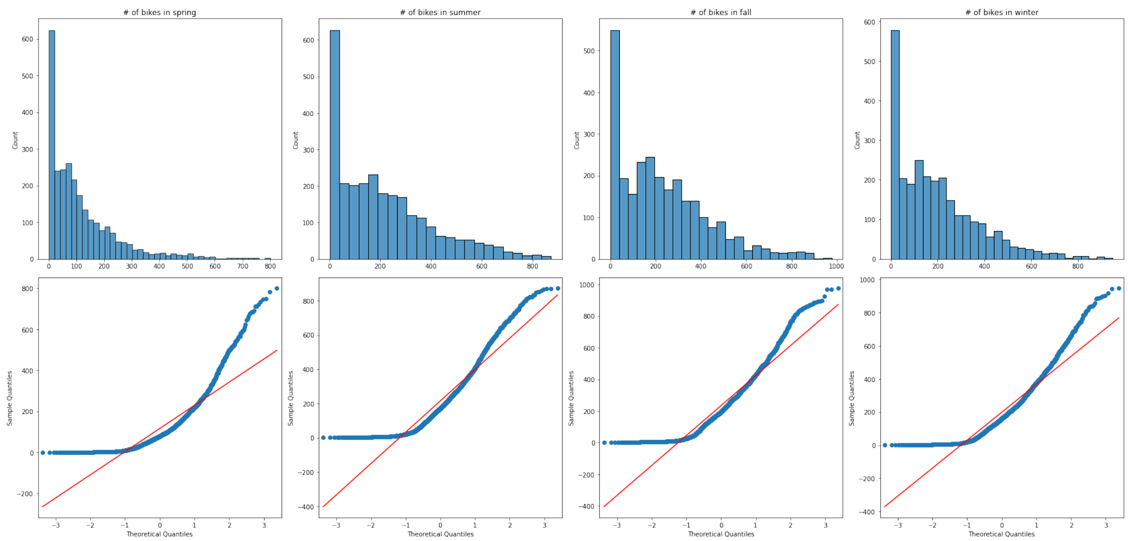
5.4.1 Checking ANOVA assumptions

[27]:
```
# Normal Assumption : The sample distributions should be normally distributed
fig,ax = plt.subplots(2,4,figsize=(25,12))
sns.histplot(bikes_on_season_type_1,ax=ax[0][0])
sns.histplot(bikes_on_season_type_2,ax=ax[0][1])
sns.histplot(bikes_on_season_type_3,ax=ax[0][2])
```

```
sns.histplot(bikes_on_season_type_4,ax=ax[0][3])
ax[0][0].set_title('# of bikes in spring')
ax[0][1].set_title('# of bikes in summer')
ax[0][2].set_title('# of bikes in fall')
ax[0][3].set_title('# of bikes in winter')

qqplot(bikes_on_season_type_1,line='r',ax=ax[1][0])
qqplot(bikes_on_season_type_2,line='r',ax=ax[1][1])
qqplot(bikes_on_season_type_3,line='r',ax=ax[1][2])
qqplot(bikes_on_season_type_4,line='r',ax=ax[1][3])

plt.show()
```



- We can see from above graphs that none of the distributions are normal

[28]:
```
# Equal Variance Assumption : The sample distribution should have equal variance
# Null hypothesis : There is no difference of standard deviation between the samples
# Alternate hypothesis : There is a difference of standard deviation between the samples
# We can do a levene test to check this at a significance level of 5%

levene(bikes_on_season_type_1, bikes_on_season_type_2, bikes_on_season_type_3, bikes_on_season_type_4)
```

[28]:
```
LeveneResult(statistic=187.7706624026276, pvalue=1.0147116860043298e-118)
```

- The levene test gives a pvalue of ~0% which is much less than our significance level
- Hence we can reject the null hypothesis
- Hence we can say that these distributions have different standard deviations

[29]:
```python
# We will now do one way ANOVA to check difference between means
f_oneway(bikes_on_season_type_1, bikes_on_season_type_2,␣
↪bikes_on_season_type_3, bikes_on_season_type_4)
```

[29]: F_onewayResult(statistic=236.94671081032106, pvalue=6.164843386499654e-149)

- We get a fstat of 236.9
- Our pvalue is ~0% which is much lower than our significance level of 5%
- We reject the H0
- We can infer that season has a significant effect on number of bikes rented

5.5 Are there more bikes rented in summer and fall?

- H0 : Summer and Fall season has no effect on number of bikes rented
- Ha : Summer and Fall season increases the number of bikes rented
- Significance level : 5%
- Test Statistic : t-test score (2 sample t-test)

[30]:
```python
bikes_on_season_type_2_and_3 = np.concatenate((bikes_on_season_type_2,␣
↪bikes_on_season_type_3))
bikes_on_season_type_1_and_4 = np.concatenate((bikes_on_season_type_1,␣
↪bikes_on_season_type_4))
```

[31]:
```python
# Checking ttest assumptions
# Equal Variance Assumption : The sample distribution should have equal variance
# Null hypothesis : There is no difference of standard deviation between the␣
↪samples
# Alternate hypothesis : There is a difference of standard deviation between␣
↪the samples
# We can do a levene test to check this at a significance level of 5%

levene(bikes_on_season_type_2_and_3, bikes_on_season_type_1_and_4)
```

[31]: LeveneResult(statistic=237.21717358575066, pvalue=5.74764555857786e-53)

- The levene test gives a pvalue of ~0% which is much less than our significance level
- Hence we can reject the null hypothesis
- Hence we can say that these distributions have different standard deviations
- Hence we will do a Welch t-test instead here

[32]:
```python
# We will do a 2 sample Welch t-test to check if these two are independent or␣
↪not
ttest_ind(bikes_on_season_type_2_and_3, bikes_on_season_type_1_and_4,␣
↪alternative='greater', equal_var=False)
```

[32]: Ttest_indResult(statistic=19.589523172181725, pvalue=2.9605129625749147e-84)

- We get a t-test score of 19.5
- Our pvalue is ~0% which is much lower than our significance level of 5%
- We can reject the H0
- We can infer that summer and fall season is linked to increase in number of bikes rented

---

5.6 Is weather dependent on season?

[33]:
```
df_copy['weather'].value_counts()
```

[33]:
```
1    7192
2    2834
3     859
4       1
Name: weather, dtype: int64
```

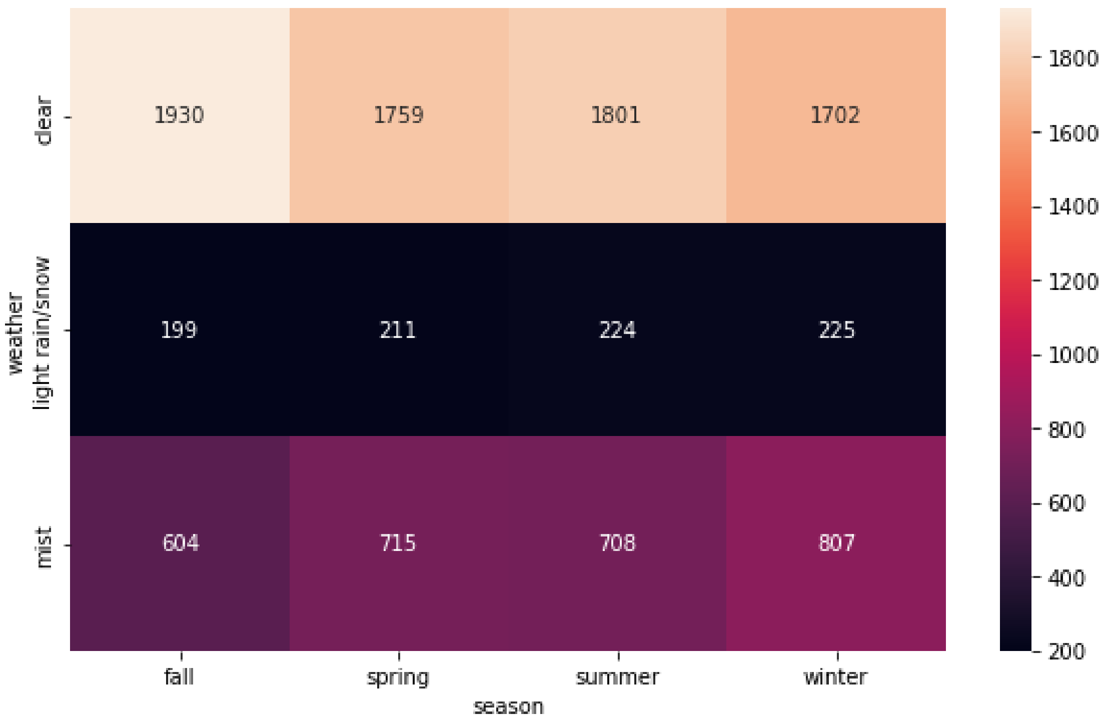
- Again dropping the weather type 4 before doing the test
- In chi2 test we also require atleast 5 samples in each category

- H0 : Season has no effect on the weather
- Ha : Season has an effect on the weather
- Significance level : 5%
- Test Statistic : chi-statistic

[34]:
```
df_copy = df_copy[df_copy['weather'] != 4]
df = df[df['weather'] != 'heavy rain/snow']
```

[35]:
```
#Lets look at a crosstab between weather and season
plt.rcParams['figure.figsize'] = (8,5)
sns.heatmap(pd.crosstab(df['weather'], df['season']),annot=True,fmt='d')
```

[35]:
```
<AxesSubplot:xlabel='season', ylabel='weather'>
```



[36]:
```
# We will do a chi sqaure test to see if these two features are dependent or not
chi2_contingency(pd.crosstab(df_copy['weather'], df_copy['season']))
```

[36]:
```
(46.101457310732485,
 2.8260014509929403e-08,
 6,
 array([[1774.04869086, 1805.76352779, 1805.76352779, 1806.42425356],
        [ 699.06201194,  711.55920992,  711.55920992,  711.81956821],
        [ 211.8892972 ,  215.67726229,  215.67726229,  215.75617823]]))
```

- We get a chisquare-stat of 46.1
- Our pvalue is ~0% which is much lower than our significance level of 5%
- We reject the H0
- We can infer that season has a significant effect on the weather