



WELCOME!

Welcome to "Bike Demand Visualization Project" which is the capstone project of Data Visualization Lessons . As you know recently, free or affordable access to bicycles has been provided for short-distance trips in an urban area as an alternative to motorized public transport or private vehicles. Thus, it is aimed to reduce traffic congestion, noise and air pollution.

The aim of this project is to reveal the current patterns in the data by showing the historical data of London bike shares with visualization tools.

This will allow us to X-ray the data as part of the EDA process before setting up a machine learning model.

Determines

Features

- timestamp - timestamp field for grouping the data
- cnt - the count of a new bike shares
- t1 - real temperature in C
- t2 - temperature in C "feels like"
- hum - humidity in percentage
- wind_speed - wind speed in km/h
- weather_code - category of the weather
- is_holiday - boolean field - 1 holiday / 0 non holiday
- is_weekend - boolean field - 1 if the day is weekend
- season - category field meteorological seasons: 0-spring ; 1-summer; 2-fall; 3-winter.

"weather_code" category description:

- 1 = Clear ; mostly clear but have some values with haze/fog/patches of fog/ fog in vicinity
- 2 = scattered clouds / few clouds
- 3 = Broken clouds
- 4 = Cloudy
- 7 = Rain/ light Rain shower/ Light rain
- 10 = rain with thunderstorm
- 26 = snowfall
- 94 = Freezing Fog

Initially, the task of discovering data will be waiting for you as always. Recognize features, detect missing values, outliers etc. Review the data from various angles in different time breakdowns. For example, visualize the distribution of bike shares by day of the week. With this graph, you will be able to easily observe and make inferences how people's behavior changes daily. Likewise, you can make hourly, monthly, seasonally etc. analyzes. In addition, you can analyze correlation of variables with a heatmap.

Tasks

1. Import Libraries

In [1]:

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

%matplotlib inline

#import warnings ;
#warnings.filterwarnings("ignore")
```

2. Read Dataset

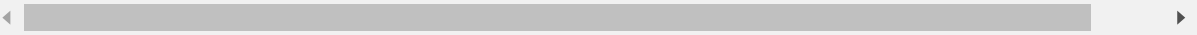
In [2]:

```
df = pd.read_csv(r"C:\Users\EmincanY\Desktop\TecPro Group\store_sharing.csv")
df
```

Out[2]:

	timestamp	cnt	t1	t2	hum	wind_speed	weather_code	is_holiday	is_weekend	s
0	2015-01-04 00:00:00	182	3.0	2.0	93.0	6.0	3.0	0.0	1.0	
1	2015-01-04 01:00:00	138	3.0	2.5	93.0	5.0	1.0	0.0	1.0	
2	2015-01-04 02:00:00	134	2.5	2.5	96.5	0.0	1.0	0.0	1.0	
3	2015-01-04 03:00:00	72	2.0	2.0	100.0	0.0	1.0	0.0	1.0	
4	2015-01-04 04:00:00	47	2.0	0.0	93.0	6.5	1.0	0.0	1.0	
...
17409	2017-01-03 19:00:00	1042	5.0	1.0	81.0	19.0	3.0	0.0	0.0	
17410	2017-01-03 20:00:00	541	5.0	1.0	81.0	21.0	4.0	0.0	0.0	
17411	2017-01-03 21:00:00	337	5.5	1.5	78.5	24.0	4.0	0.0	0.0	
17412	2017-01-03 22:00:00	224	5.5	1.5	76.0	23.0	4.0	0.0	0.0	
17413	2017-01-03 23:00:00	139	5.0	1.0	76.0	22.0	2.0	0.0	0.0	

17414 rows × 10 columns



3. Check missing values and if there are any duplicate rows or not.

In [3]:

```
df.isnull().sum() # There is no any nan value.
```

Out[3]:

```
timestamp    0
cnt          0
t1           0
t2           0
hum          0
wind_speed   0
weather_code  0
is_holiday   0
is_weekend   0
season       0
dtype: int64
```

In [4]:

```
df.drop_duplicates() # There is no duplicate rows. No one dropped.
```

Out[4]:

	timestamp	cnt	t1	t2	hum	wind_speed	weather_code	is_holiday	is_weekend	s
0	2015-01-04 00:00:00	182	3.0	2.0	93.0	6.0	3.0	0.0	1.0	
1	2015-01-04 01:00:00	138	3.0	2.5	93.0	5.0	1.0	0.0	1.0	
2	2015-01-04 02:00:00	134	2.5	2.5	96.5	0.0	1.0	0.0	1.0	
3	2015-01-04 03:00:00	72	2.0	2.0	100.0	0.0	1.0	0.0	1.0	
4	2015-01-04 04:00:00	47	2.0	0.0	93.0	6.5	1.0	0.0	1.0	
...
17409	2017-01-03 19:00:00	1042	5.0	1.0	81.0	19.0	3.0	0.0	0.0	
17410	2017-01-03 20:00:00	541	5.0	1.0	81.0	21.0	4.0	0.0	0.0	
17411	2017-01-03 21:00:00	337	5.5	1.5	78.5	24.0	4.0	0.0	0.0	
17412	2017-01-03 22:00:00	224	5.5	1.5	76.0	23.0	4.0	0.0	0.0	
17413	2017-01-03 23:00:00	139	5.0	1.0	76.0	22.0	2.0	0.0	0.0	

17414 rows × 10 columns



4. Plot the distribution of various discrete features on (Season, haliday, weekend and weathercode)

In [46]:

```
#mapping = {0.0 : "Spring" , 1.0 : "Summer" , 2.0 : "Fall" , 3.0 : "Winter"}
#df["season_name"] = df.season.map(mapping)
```

```
fig, ax = plt.subplots(2,2 , figsize = (25,15))
```

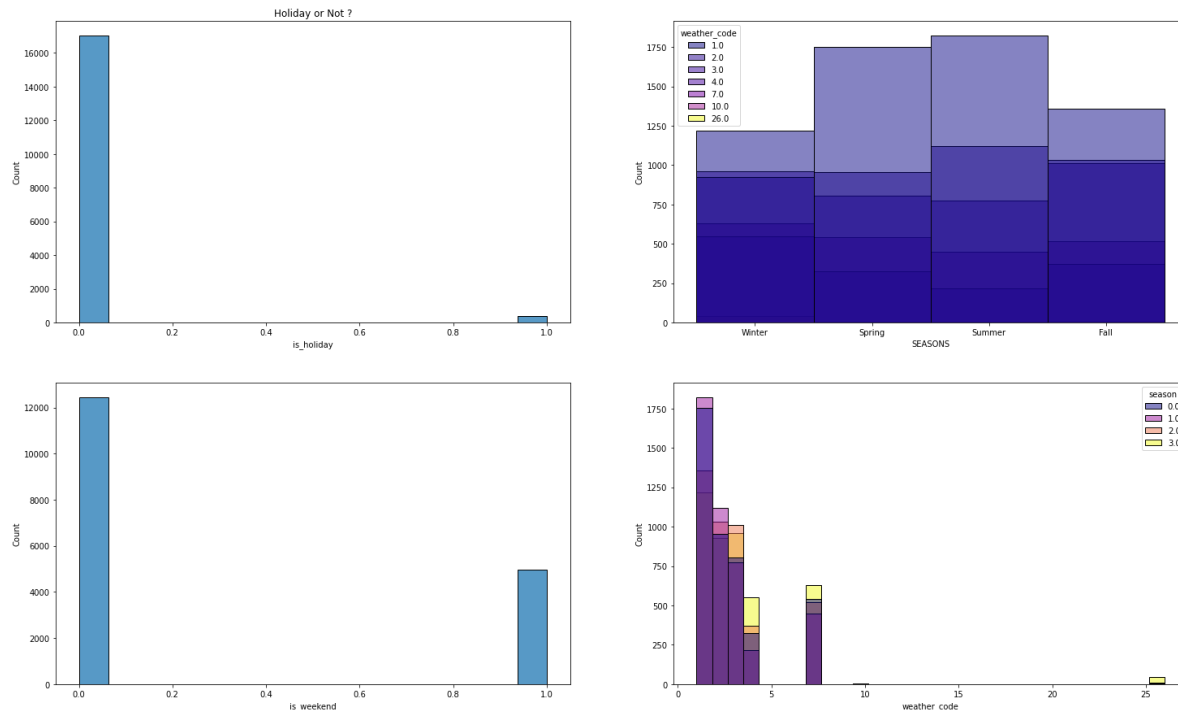
```
a = sns.histplot(ax = ax[0][0] , data = df , x = "is_holiday" )
a.set_title("Holiday or Not ?") # Değişkene atayım set yap.
```

```
b = sns.histplot(data = df , x = "season_name" , ax = ax[0][1] , hue = "weather_code" , pal
b.set_xlabel("SEASONS")
```

```
#c = sns.histplot(x = df["is_weekend"] , ax = ax[1][0] , hue = df["weather_code"] )
```

```
c = sns.histplot( x = df["is_weekend"] , ax = ax[1][0])
```

```
d = sns.histplot(x = df["weather_code"] , ax = ax[1][1] , bins = 30 , hue = df["season"] ,
```



weather_code

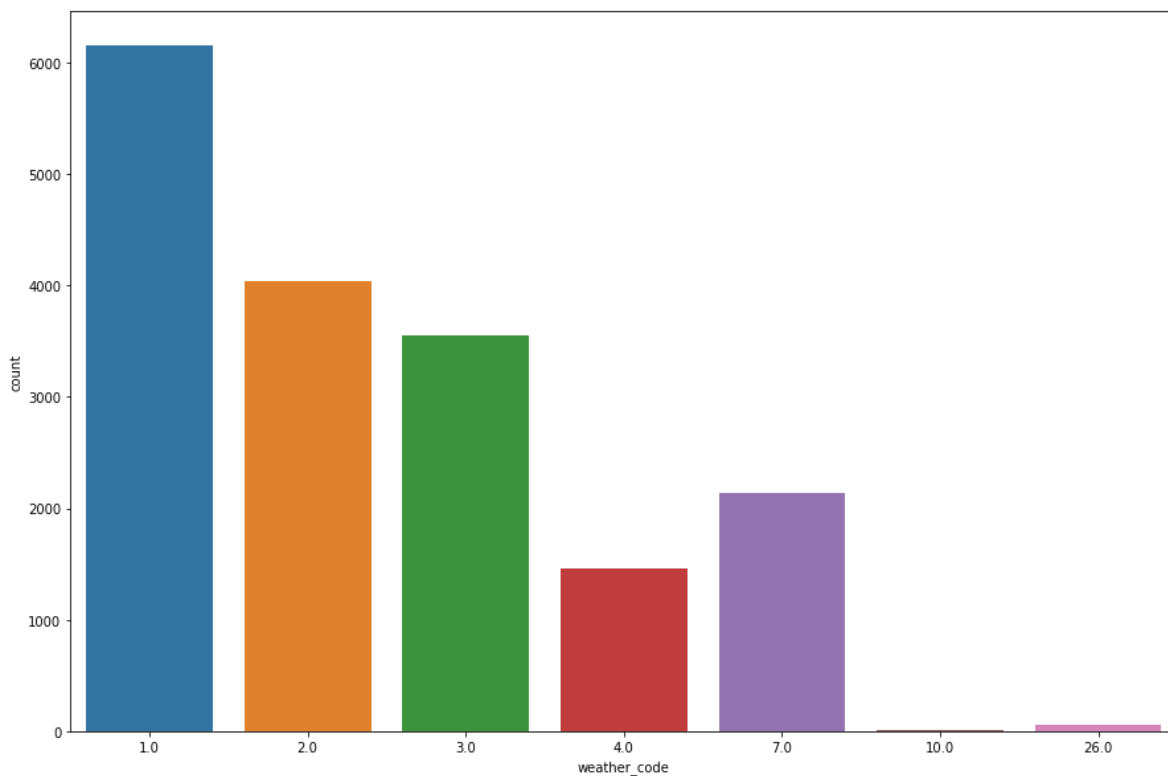
```
sns.countplot(x='weather_code',data=df)
```

1 = Clear ; mostly clear but have some values with haze/fog/patches of fog/ fog in vicinity
 2 = scattered clouds / few clouds
 3 = Broken clouds
 4 = Cloudy
 7 = Rain/ light Rain shower/ Light rain
 10 = rain with thunderstorm
 26 = snowfall
 94 = Freezing Fog

5. Look at the data type of each variable, transform timestamp in type, and set it as index.

In [6]:

```
plt.figure(figsize=(15,10))
sns.countplot(x='weather_code',data=df);
```



In [7]:

```
df.dtypes
```

Out[7]:

```
timestamp    object
cnt          int64
t1           float64
t2           float64
hum          float64
wind_speed   float64
weather_code float64
is_holiday   float64
is_weekend   float64
season       float64
season_name   object
dtype: object
```

In [8]:

```
df.head()
```

Out[8]:

	timestamp	cnt	t1	t2	hum	wind_speed	weather_code	is_holiday	is_weekend	season
0	2015-01-04 00:00:00	182	3.0	2.0	93.0	6.0	3.0	0.0	1.0	3.0
1	2015-01-04 01:00:00	138	3.0	2.5	93.0	5.0	1.0	0.0	1.0	3.0
2	2015-01-04 02:00:00	134	2.5	2.5	96.5	0.0	1.0	0.0	1.0	3.0
3	2015-01-04 03:00:00	72	2.0	2.0	100.0	0.0	1.0	0.0	1.0	3.0
4	2015-01-04 04:00:00	47	2.0	0.0	93.0	6.5	1.0	0.0	1.0	3.0

In [9]:

```
df["timestamp"] = df.timestamp.astype("datetime64") #df['timestamp'] = pd.to_datetime(df['timestamp'])
df.dtypes
```

Out[9]:

```
timestamp      datetime64[ns]
cnt              int64
t1              float64
t2              float64
hum             float64
wind_speed      float64
weather_code    float64
is_holiday      float64
is_weekend      float64
season          float64
season_name     object
dtype: object
```

In [10]:

```
df.set_index("timestamp", inplace = True)
```

6. Make feature engineering. Extract new columns (day of the week, day of the month, hour, month, season, year etc.)


```
year = now.strftime("%Y")
```

Contains formatted string.

Format code. %Y formats to year.

In [11]:

```
df
```

Out[11]:

	cnt	t1	t2	hum	wind_speed	weather_code	is_holiday	is_weekend	season
timestamp									
2015-01-04 00:00:00	182	3.0	2.0	93.0	6.0	3.0	0.0	1.0	3.0
2015-01-04 01:00:00	138	3.0	2.5	93.0	5.0	1.0	0.0	1.0	3.0
2015-01-04 02:00:00	134	2.5	2.5	96.5	0.0	1.0	0.0	1.0	3.0
2015-01-04 03:00:00	72	2.0	2.0	100.0	0.0	1.0	0.0	1.0	3.0
2015-01-04 04:00:00	47	2.0	0.0	93.0	6.5	1.0	0.0	1.0	3.0
...
2017-01-03 19:00:00	1042	5.0	1.0	81.0	19.0	3.0	0.0	0.0	3.0
2017-01-03 20:00:00	541	5.0	1.0	81.0	21.0	4.0	0.0	0.0	3.0
2017-01-03 21:00:00	337	5.5	1.5	78.5	24.0	4.0	0.0	0.0	3.0
2017-01-03 22:00:00	224	5.5	1.5	76.0	23.0	4.0	0.0	0.0	3.0
2017-01-03 23:00:00	139	5.0	1.0	76.0	22.0	2.0	0.0	0.0	3.0

17414 rows × 10 columns

In [12]:

```
df["year"] = df.index.year
df["month"] = df.index.month
df["day"] = df.index.day
df["hour"] = df.index.hour
```

In [13]:

```
df['dayofweek_num'] = df.index.dayofweek  
df['dayofweek_name'] = df.index.day_name()  
df["dayofmonth_num"] = df.index.strftime("%d")
```

In [14]:

```
mapping = {0.0 : "Spring" , 1.0 : "Summer" , 2.0 : "Fall" , 3.0 : "Winter"}  
df["season_name"] = df.season.map(mapping)
```

7. Visualize the correlation with a heatmap

In [15]:

df

Out[15]:

	cnt	t1	t2	hum	wind_speed	weather_code	is_holiday	is_weekend	season
timestamp									
2015-01-04 00:00:00	182	3.0	2.0	93.0	6.0	3.0	0.0	1.0	3.0
2015-01-04 01:00:00	138	3.0	2.5	93.0	5.0	1.0	0.0	1.0	3.0
2015-01-04 02:00:00	134	2.5	2.5	96.5	0.0	1.0	0.0	1.0	3.0
2015-01-04 03:00:00	72	2.0	2.0	100.0	0.0	1.0	0.0	1.0	3.0
2015-01-04 04:00:00	47	2.0	0.0	93.0	6.5	1.0	0.0	1.0	3.0
...
2017-01-03 19:00:00	1042	5.0	1.0	81.0	19.0	3.0	0.0	0.0	3.0
2017-01-03 20:00:00	541	5.0	1.0	81.0	21.0	4.0	0.0	0.0	3.0
2017-01-03 21:00:00	337	5.5	1.5	78.5	24.0	4.0	0.0	0.0	3.0
2017-01-03 22:00:00	224	5.5	1.5	76.0	23.0	4.0	0.0	0.0	3.0
2017-01-03 23:00:00	139	5.0	1.0	76.0	22.0	2.0	0.0	0.0	3.0

17414 rows × 17 columns



In [16]:

```
df.corr()
```

Out[16]:

	cnt	t1	t2	hum	wind_speed	weather_code	is_holid
cnt	1.000000	0.388798	0.369035	-0.462901	0.116295	-0.166633	-0.0516
t1	0.388798	1.000000	0.988344	-0.447781	0.145471	-0.097114	-0.0422
t2	0.369035	0.988344	1.000000	-0.403495	0.088409	-0.098385	-0.0400
hum	-0.462901	-0.447781	-0.403495	1.000000	-0.287789	0.334750	0.0320
wind_speed	0.116295	0.145471	0.088409	-0.287789	1.000000	0.124803	-0.0026
weather_code	-0.166633	-0.097114	-0.098385	0.334750	0.124803	1.000000	0.0129
is_holiday	-0.051698	-0.042233	-0.040051	0.032068	-0.002606	0.012939	1.0000
is_weekend	-0.096499	-0.005342	-0.008510	0.028098	0.011479	0.042362	-0.0948
season	-0.116180	-0.285851	-0.285900	0.290381	0.010305	0.098976	-0.0324
year	0.010046	-0.037959	-0.044972	0.072443	-0.094739	-0.009234	0.0346
month	0.063757	0.332712	0.368366	0.113149	-0.086383	-0.033253	-0.0115
day	-0.017887	0.005072	0.006791	-0.020868	0.002040	0.001904	0.0426
hour	0.324423	0.168708	0.153956	-0.295653	0.141792	-0.041786	-0.0002
dayofweek_num	-0.068688	-0.002317	-0.006824	0.011556	0.001708	0.020619	-0.1446

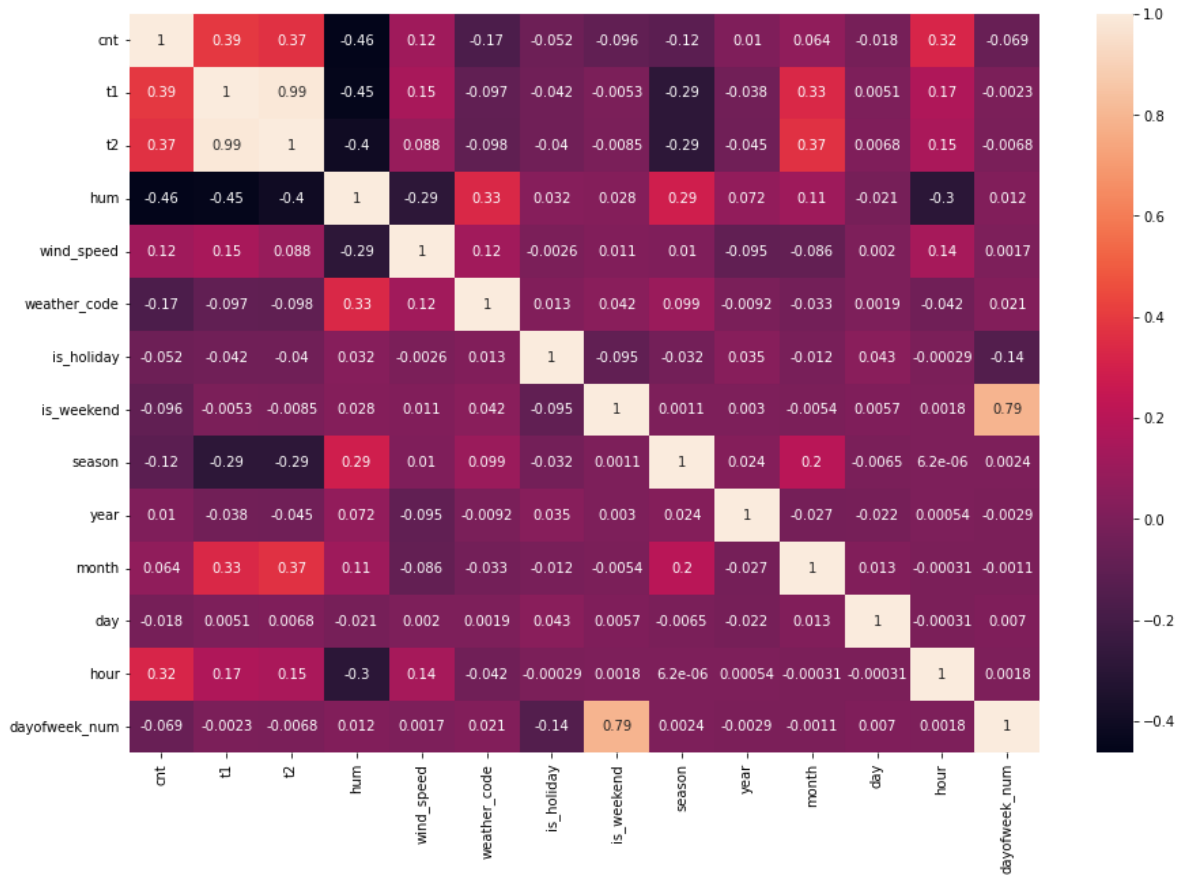


In [17]:

```
from matplotlib.pyplot import annotate

plt.figure(figsize= (15,10))

sns.heatmap(df.corr() , annot = True);
```



8. Visualize the correlation of the target variable and the other features with barplot

```
# Make up 3000 rows
df = pd.DataFrame({'date': ['3/11/2000', '3/12/2000', '3/13/2000'] * 1000 })

%timeit pd.to_datetime(df['date'], infer_datetime_format=True)
100 loops, best of 3: 10.4 ms per loop

%timeit pd.to_datetime(df['date'], infer_datetime_format=False)
1 loop, best of 3: 471 ms per loop
```

In [18]:

df.corr()

Out[18]:

	cnt	t1	t2	hum	wind_speed	weather_code	is_holid
cnt	1.000000	0.388798	0.369035	-0.462901	0.116295	-0.166633	-0.0516
t1	0.388798	1.000000	0.988344	-0.447781	0.145471	-0.097114	-0.0422
t2	0.369035	0.988344	1.000000	-0.403495	0.088409	-0.098385	-0.0400
hum	-0.462901	-0.447781	-0.403495	1.000000	-0.287789	0.334750	0.0320
wind_speed	0.116295	0.145471	0.088409	-0.287789	1.000000	0.124803	-0.0026
weather_code	-0.166633	-0.097114	-0.098385	0.334750	0.124803	1.000000	0.0129
is_holiday	-0.051698	-0.042233	-0.040051	0.032068	-0.002606	0.012939	1.0000
is_weekend	-0.096499	-0.005342	-0.008510	0.028098	0.011479	0.042362	-0.0948
season	-0.116180	-0.285851	-0.285900	0.290381	0.010305	0.098976	-0.0324
year	0.010046	-0.037959	-0.044972	0.072443	-0.094739	-0.009234	0.0346
month	0.063757	0.332712	0.368366	0.113149	-0.086383	-0.033253	-0.0115
day	-0.017887	0.005072	0.006791	-0.020868	0.002040	0.001904	0.0426
hour	0.324423	0.168708	0.153956	-0.295653	0.141792	-0.041786	-0.0002
dayofweek_num	-0.068688	-0.002317	-0.006824	0.011556	0.001708	0.020619	-0.1446

In [19]:

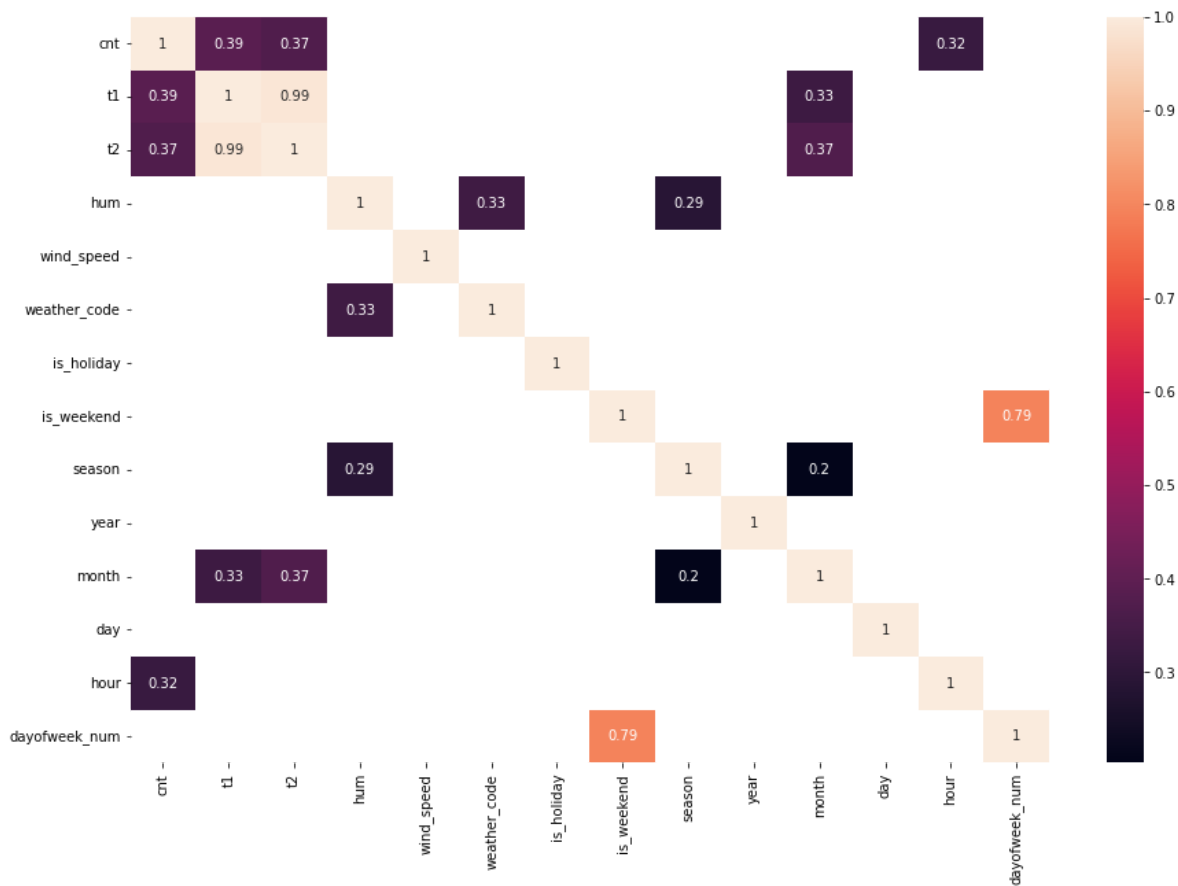
df.corr()[df.corr() > 0.2]

Out[19]:

	cnt	t1	t2	hum	wind_speed	weather_code	is_holiday
cnt	1.000000	0.388798	0.369035	NaN	NaN	NaN	NaN
t1	0.388798	1.000000	0.988344	NaN	NaN	NaN	NaN
t2	0.369035	0.988344	1.000000	NaN	NaN	NaN	NaN
hum	NaN	NaN	NaN	1.000000	NaN	0.33475	NaN
wind_speed	NaN	NaN	NaN	NaN	1.0	NaN	NaN
weather_code	NaN	NaN	NaN	0.334750	NaN	1.00000	NaN
is_holiday	NaN	NaN	NaN	NaN	NaN	NaN	1.0
is_weekend	NaN	NaN	NaN	NaN	NaN	NaN	NaN
season	NaN	NaN	NaN	0.290381	NaN	NaN	NaN
year	NaN	NaN	NaN	NaN	NaN	NaN	NaN
month	NaN	0.332712	0.368366	NaN	NaN	NaN	NaN
day	NaN	NaN	NaN	NaN	NaN	NaN	NaN
hour	0.324423	NaN	NaN	NaN	NaN	NaN	NaN
dayofweek_num	NaN	NaN	NaN	NaN	NaN	NaN	NaN

In [20]:

```
plt.figure(figsize=(15,10))
sns.heatmap(df.corr()[df.corr() > 0.2] , annot = True);
```



In [21]:

```
df.cnt.index
```

Out[21]:

```
DatetimeIndex(['2015-01-04 00:00:00', '2015-01-04 01:00:00',
               '2015-01-04 02:00:00', '2015-01-04 03:00:00',
               '2015-01-04 04:00:00', '2015-01-04 05:00:00',
               '2015-01-04 06:00:00', '2015-01-04 07:00:00',
               '2015-01-04 08:00:00', '2015-01-04 09:00:00',
               ...,
               '2017-01-03 14:00:00', '2017-01-03 15:00:00',
               '2017-01-03 16:00:00', '2017-01-03 17:00:00',
               '2017-01-03 18:00:00', '2017-01-03 19:00:00',
               '2017-01-03 20:00:00', '2017-01-03 21:00:00',
               '2017-01-03 22:00:00', '2017-01-03 23:00:00'],
              dtype='datetime64[ns]', name='timestamp', length=17414, freq=N
              one)
```

In [22]:

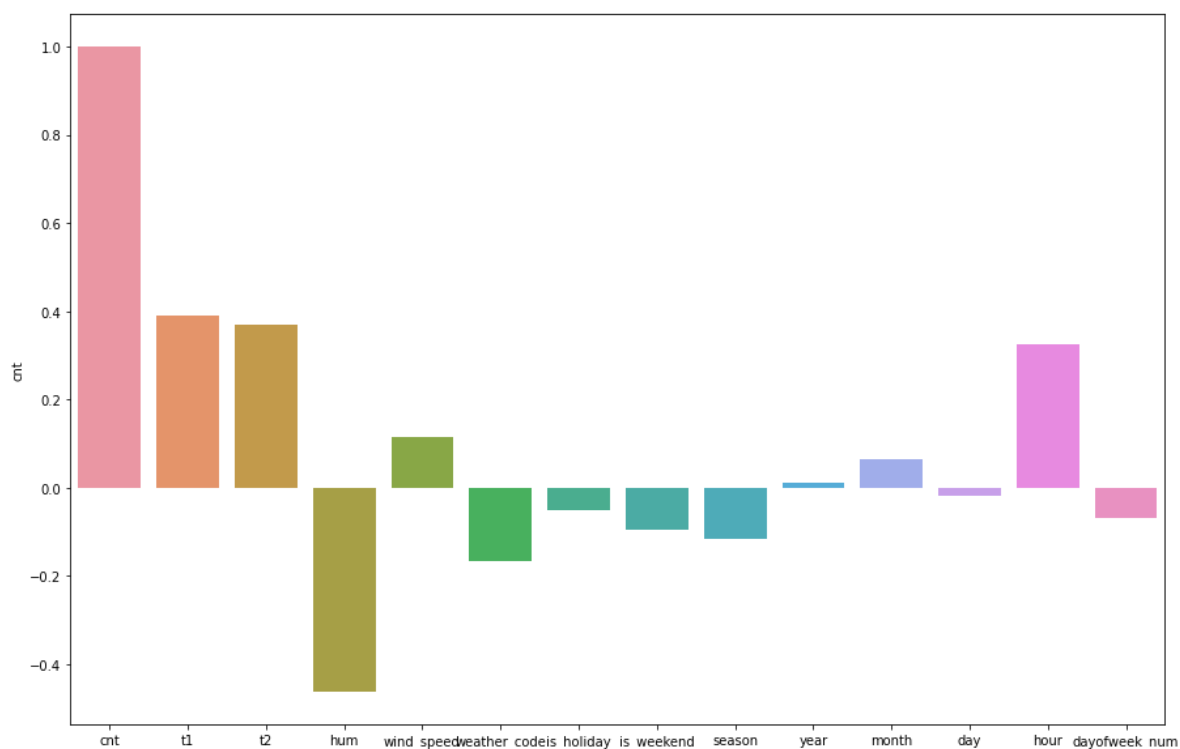
```
cnt_cor = df.corr()["cnt"].sort_values()  
cnt_cor
```

Out[22]:

```
hum          -0.462901  
weather_code -0.166633  
season       -0.116180  
is_weekend   -0.096499  
dayofweek_num -0.068688  
is_holiday   -0.051698  
day          -0.017887  
year         0.010046  
month        0.063757  
wind_speed   0.116295  
hour         0.324423  
t2           0.369035  
t1           0.388798  
cnt          1.000000  
Name: cnt, dtype: float64
```

In [23]:

```
plt.figure(figsize=(15,10))  
sns.barplot(x = df.corr().cnt.index , y = df.corr().cnt );
```



9. Plot bike shares over time use lineplot.

In [24]:

```
df.head()
```

Out[24]:

	cnt	t1	t2	hum	wind_speed	weather_code	is_holiday	is_weekend	season	s
timestamp										
2015-01-04 00:00:00	182	3.0	2.0	93.0	6.0	3.0	0.0	1.0	3.0	
2015-01-04 01:00:00	138	3.0	2.5	93.0	5.0	1.0	0.0	1.0	3.0	
2015-01-04 02:00:00	134	2.5	2.5	96.5	0.0	1.0	0.0	1.0	3.0	
2015-01-04 03:00:00	72	2.0	2.0	100.0	0.0	1.0	0.0	1.0	3.0	
2015-01-04 04:00:00	47	2.0	0.0	93.0	6.5	1.0	0.0	1.0	3.0	

In [25]:

```
df.index.year
```

Out[25]:

```
Int64Index([2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015,
            ...,
            2017, 2017, 2017, 2017, 2017, 2017, 2017, 2017, 2017, 2017],
            dtype='int64', name='timestamp', length=17414)
```

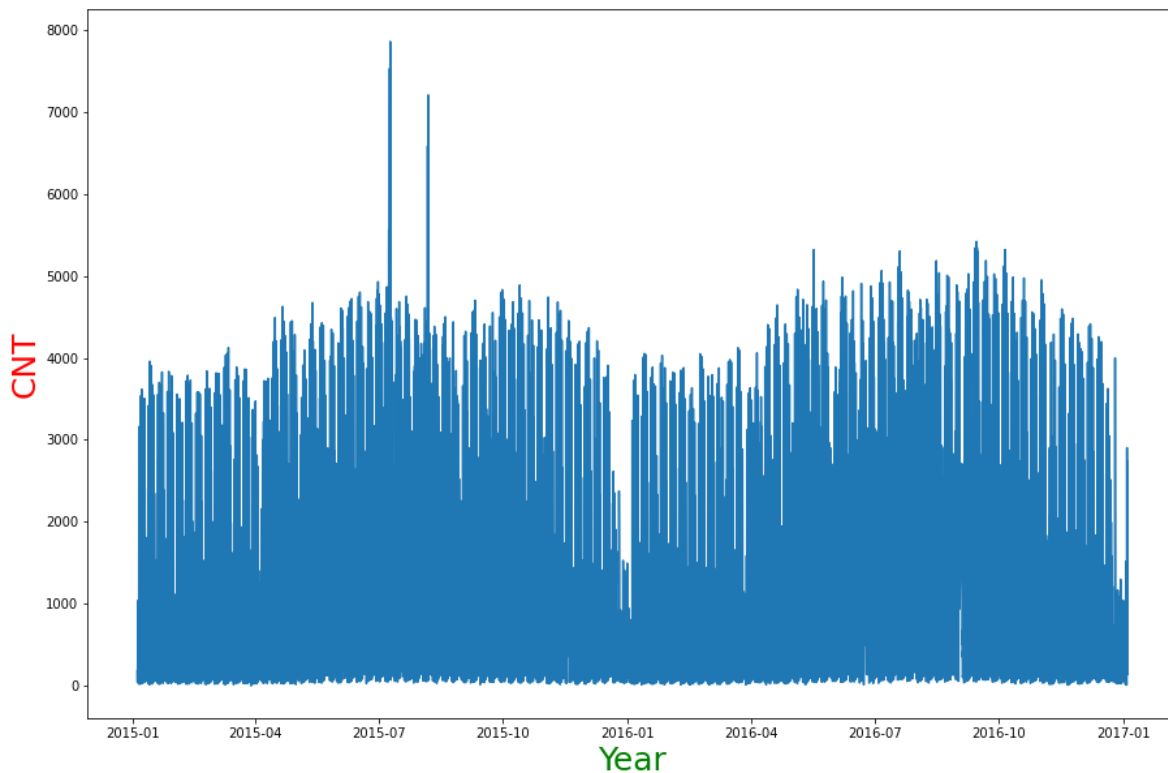
In [26]:

```
from turtle import color

plt.figure(figsize=(15,10));

sns.lineplot(x = df.index , y =df["cnt"]);

plt.xlabel("Year" , fontsize = 25 , color = "green");
plt.ylabel("CNT" , fontsize = 25 , color = "red");
```



10. Plot bike shares by months and year_of_month (use lineplot, pointplot, barplot).

In [27]:

df

Out[27]:

	cnt	t1	t2	hum	wind_speed	weather_code	is_holiday	is_weekend	season
timestamp									
2015-01-04 00:00:00	182	3.0	2.0	93.0	6.0	3.0	0.0	1.0	3.0
2015-01-04 01:00:00	138	3.0	2.5	93.0	5.0	1.0	0.0	1.0	3.0
2015-01-04 02:00:00	134	2.5	2.5	96.5	0.0	1.0	0.0	1.0	3.0
2015-01-04 03:00:00	72	2.0	2.0	100.0	0.0	1.0	0.0	1.0	3.0
2015-01-04 04:00:00	47	2.0	0.0	93.0	6.5	1.0	0.0	1.0	3.0
...
2017-01-03 19:00:00	1042	5.0	1.0	81.0	19.0	3.0	0.0	0.0	3.0
2017-01-03 20:00:00	541	5.0	1.0	81.0	21.0	4.0	0.0	0.0	3.0
2017-01-03 21:00:00	337	5.5	1.5	78.5	24.0	4.0	0.0	0.0	3.0
2017-01-03 22:00:00	224	5.5	1.5	76.0	23.0	4.0	0.0	0.0	3.0
2017-01-03 23:00:00	139	5.0	1.0	76.0	22.0	2.0	0.0	0.0	3.0

17414 rows × 17 columns



In [28]:

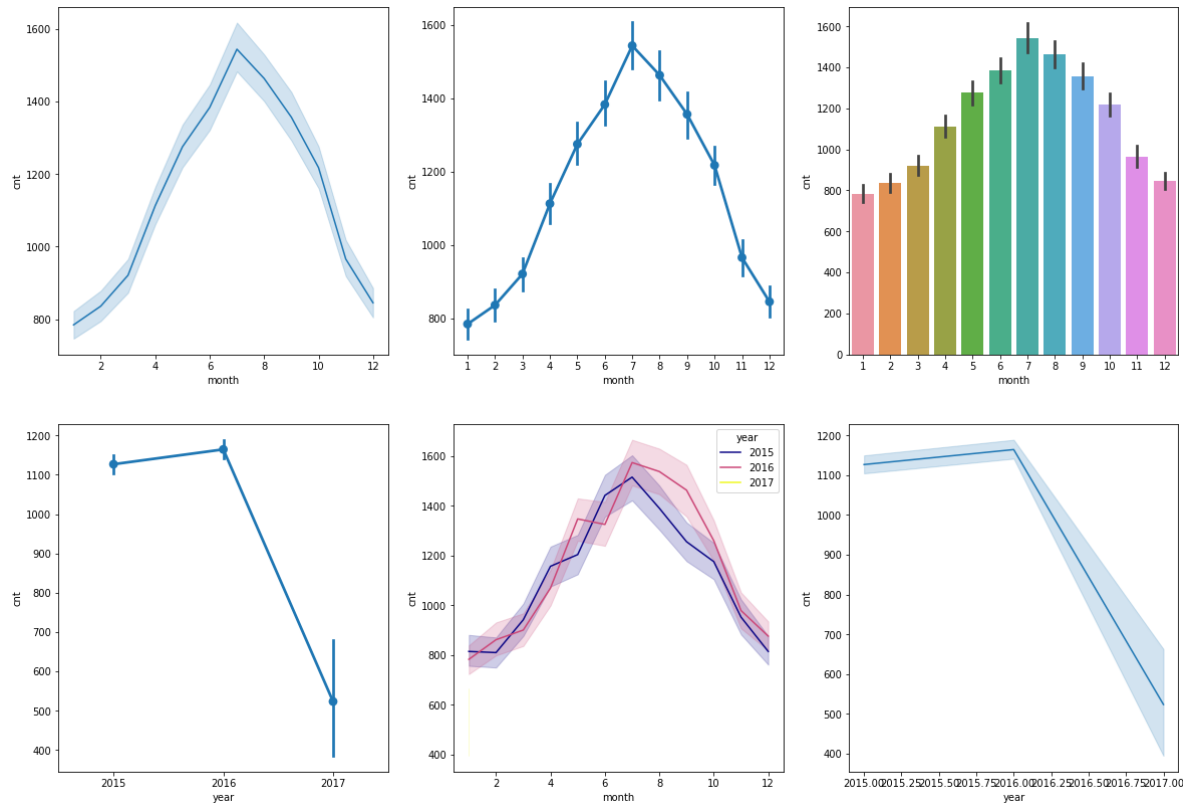
```

from matplotlib.pyplot import xlabel, ylabel

fig, ax = plt.subplots(2,3 , figsize = (20,14))

sns.lineplot( x = df["month"] , y = df["cnt"], ax = ax[0][0]);
sns.pointplot( x = df["month"] , y = df["cnt"], ax = ax[0][1]);
sns.barplot( x = df["month"] , y = df["cnt"], ax = ax[0][2]);
sns.pointplot( x = df["year"] , y = df["cnt"], ax = ax[1][0]);
sns.lineplot( x = df["month"] , y = df["cnt"] , hue = df["year"] , palette = "plasma" , ax
sns.lineplot( x = df["year"] , y = df["cnt"], ax = ax[1][2]);

```



11. Plot bike shares by hours on (holidays, weekend, season).

In [29]:

```
df
```

Out[29]:

	cnt	t1	t2	hum	wind_speed	weather_code	is_holiday	is_weekend	season
timestamp									
2015-01-04 00:00:00	182	3.0	2.0	93.0	6.0	3.0	0.0	1.0	3.0
2015-01-04 01:00:00	138	3.0	2.5	93.0	5.0	1.0	0.0	1.0	3.0
2015-01-04 02:00:00	134	2.5	2.5	96.5	0.0	1.0	0.0	1.0	3.0
2015-01-04 03:00:00	72	2.0	2.0	100.0	0.0	1.0	0.0	1.0	3.0
2015-01-04 04:00:00	47	2.0	0.0	93.0	6.5	1.0	0.0	1.0	3.0
...
2017-01-03 19:00:00	1042	5.0	1.0	81.0	19.0	3.0	0.0	0.0	3.0
2017-01-03 20:00:00	541	5.0	1.0	81.0	21.0	4.0	0.0	0.0	3.0
2017-01-03 21:00:00	337	5.5	1.5	78.5	24.0	4.0	0.0	0.0	3.0
2017-01-03 22:00:00	224	5.5	1.5	76.0	23.0	4.0	0.0	0.0	3.0
2017-01-03 23:00:00	139	5.0	1.0	76.0	22.0	2.0	0.0	0.0	3.0

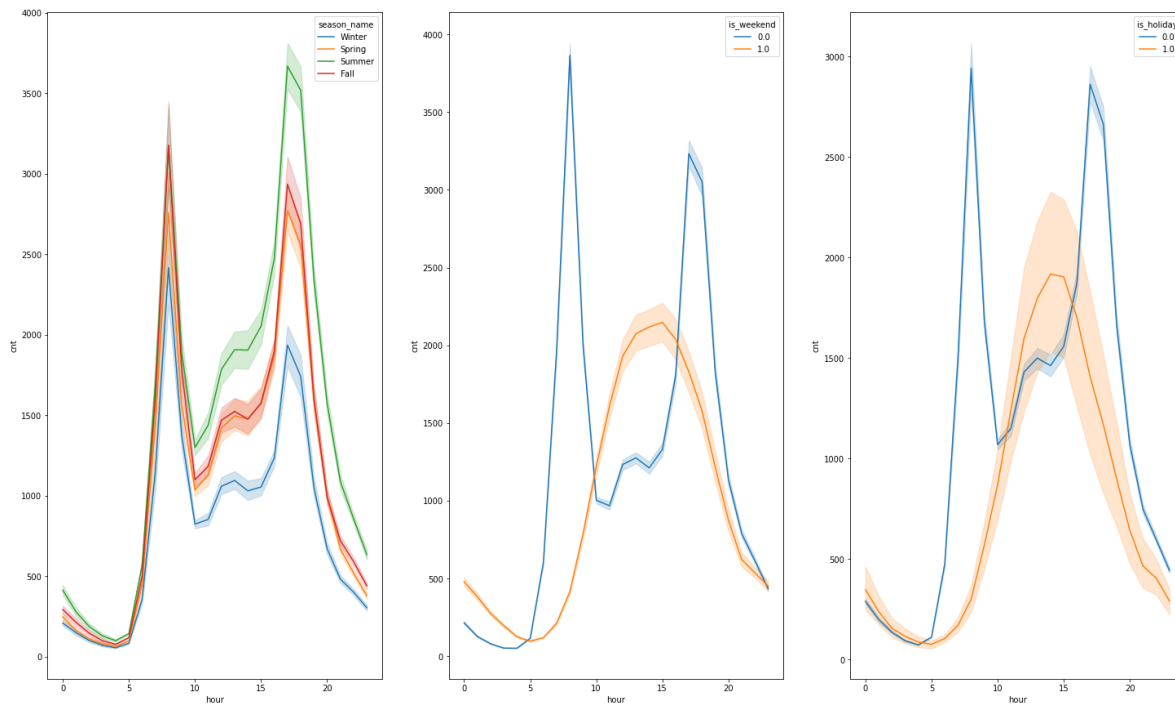
17414 rows × 17 columns



In [30]:

```
fig, ax = plt.subplots(1,3 , figsize = (25,15))

sns.lineplot(x = df.hour , y = df.cnt , hue = df.season_name , ax = ax[0]);
sns.lineplot(x = df.hour , y = df.cnt , hue = df["is_weekend"] , ax = ax[1]);
sns.lineplot(x = df.hour , y = df.cnt , hue = df["is_holiday"] ,ax = ax[2]);
```



In [31]:

```
#fig, ax = plt.subplots(1,3,figsize = (20,14))

#sns.lineplot( x = df["is_holiday"] , y = df["cnt"] , ax = ax[0]);
#sns.lineplot( x = df["is_weekend"] , y = df["cnt"] , ax = ax[1]);
#sns.lineplot( x = df["season_name"] , y = df["cnt"], ax = ax[2]);
```

12. Plot bike shares by day of week.

- You may want to see whether it is a holiday or not

In [32]:

```
df
```

Out[32]:

	cnt	t1	t2	hum	wind_speed	weather_code	is_holiday	is_weekend	season
timestamp									
2015-01-04 00:00:00	182	3.0	2.0	93.0	6.0	3.0	0.0	1.0	3.0
2015-01-04 01:00:00	138	3.0	2.5	93.0	5.0	1.0	0.0	1.0	3.0
2015-01-04 02:00:00	134	2.5	2.5	96.5	0.0	1.0	0.0	1.0	3.0
2015-01-04 03:00:00	72	2.0	2.0	100.0	0.0	1.0	0.0	1.0	3.0
2015-01-04 04:00:00	47	2.0	0.0	93.0	6.5	1.0	0.0	1.0	3.0
...
2017-01-03 19:00:00	1042	5.0	1.0	81.0	19.0	3.0	0.0	0.0	3.0
2017-01-03 20:00:00	541	5.0	1.0	81.0	21.0	4.0	0.0	0.0	3.0
2017-01-03 21:00:00	337	5.5	1.5	78.5	24.0	4.0	0.0	0.0	3.0
2017-01-03 22:00:00	224	5.5	1.5	76.0	23.0	4.0	0.0	0.0	3.0
2017-01-03 23:00:00	139	5.0	1.0	76.0	22.0	2.0	0.0	0.0	3.0

17414 rows × 17 columns

In [33]:

```
df.groupby("is_holiday")["cnt"].mean()
```

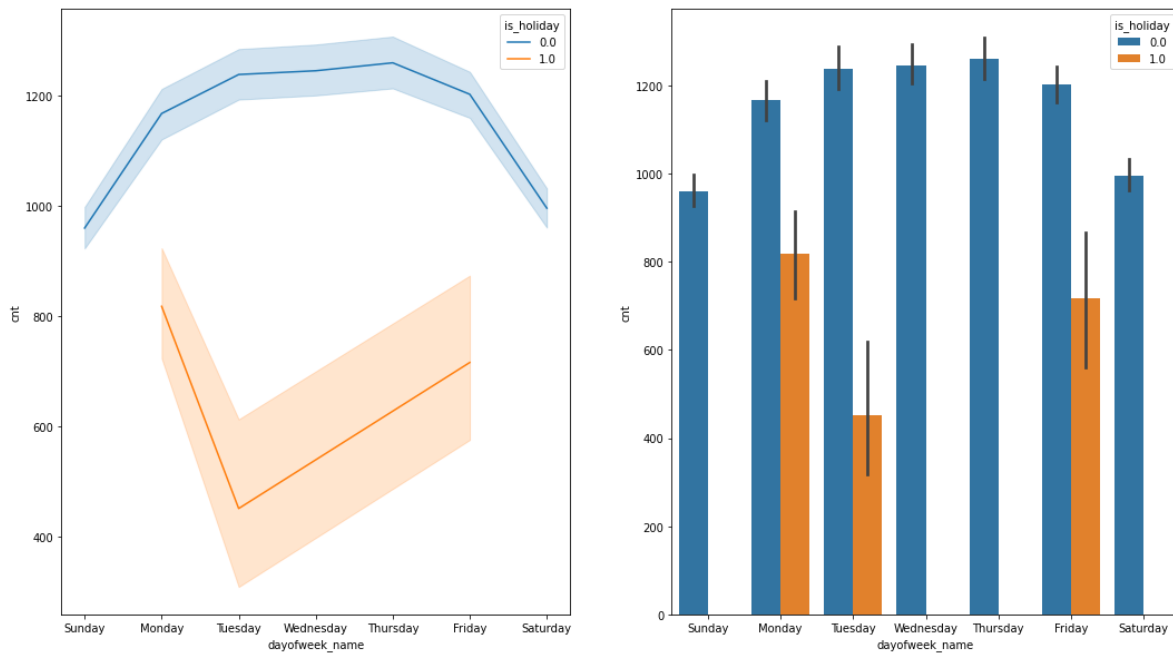
Out[33]:

```
is_holiday
0.0      1151.525191
1.0       769.526042
Name: cnt, dtype: float64
```

In [34]:

```
fig, ax = plt.subplots(1,2,figsize = (18,10))

sns.lineplot(x= df["dayofweek_name"] , y= df["cnt"] , hue = df["is_holiday"] , ax = ax[0]);
sns.barplot(x = "dayofweek_name" , y = "cnt" , data = df , hue = "is_holiday" , ax = ax[1])
```

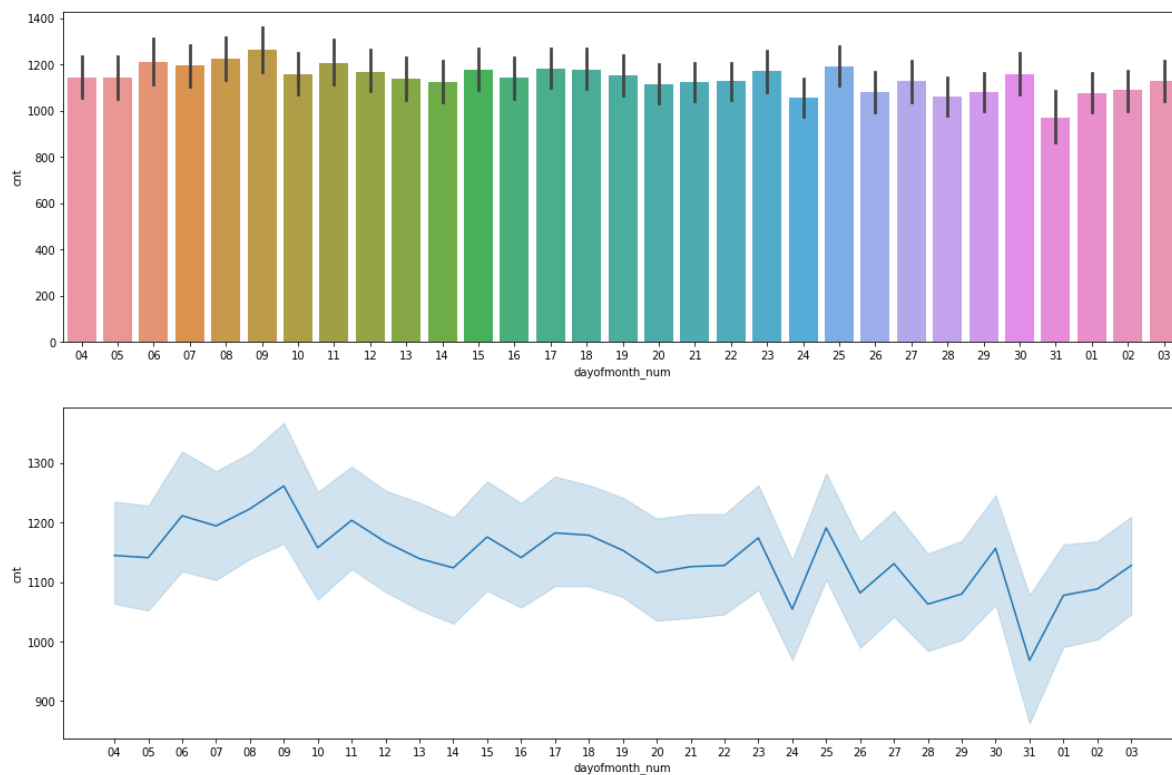


13. Plot bike shares by day of month

In [35]:

```
fig, ax = plt.subplots(2,1,figsize = (18,12))

sns.barplot(x = df["dayofmonth_num"] , y = df.cnt, ax = ax[0] ) ;
sns.lineplot(x = df["dayofmonth_num"] , y = df["cnt"] , ax = ax[1]);
```



14. Plot bike shares by year

- Plot bike shares on holidays by seasons

In [36]:

```
df[df["is_holiday"] == 1]
```

Out[36]:

	cnt	t1	t2	hum	wind_speed	weather_code	is_holiday	is_weekend	season	s
timestamp										
2015-04-03 00:00:00	279	8.0	6.0	82.0	10.0	7.0	1.0	0.0	0.0	
2015-04-03 01:00:00	174	8.0	5.5	79.0	14.0	7.0	1.0	0.0	0.0	
2015-04-03 02:00:00	89	7.5	5.5	84.5	12.0	7.0	1.0	0.0	0.0	
2015-04-03 03:00:00	61	7.0	5.0	87.0	11.0	7.0	1.0	0.0	0.0	
2015-04-03 04:00:00	46	7.0	6.0	93.0	6.0	7.0	1.0	0.0	0.0	
...	
2017-01-02 19:00:00	433	3.0	0.0	81.0	11.0	1.0	1.0	0.0	3.0	
2017-01-02 20:00:00	334	3.0	0.0	75.0	13.0	1.0	1.0	0.0	3.0	
2017-01-02 21:00:00	233	2.5	-0.5	78.0	11.0	1.0	1.0	0.0	3.0	
2017-01-02 22:00:00	201	2.0	-1.0	81.0	10.0	1.0	1.0	0.0	3.0	
2017-01-02 23:00:00	145	1.0	-2.0	93.0	10.0	1.0	1.0	0.0	3.0	

384 rows × 17 columns



In [37]:

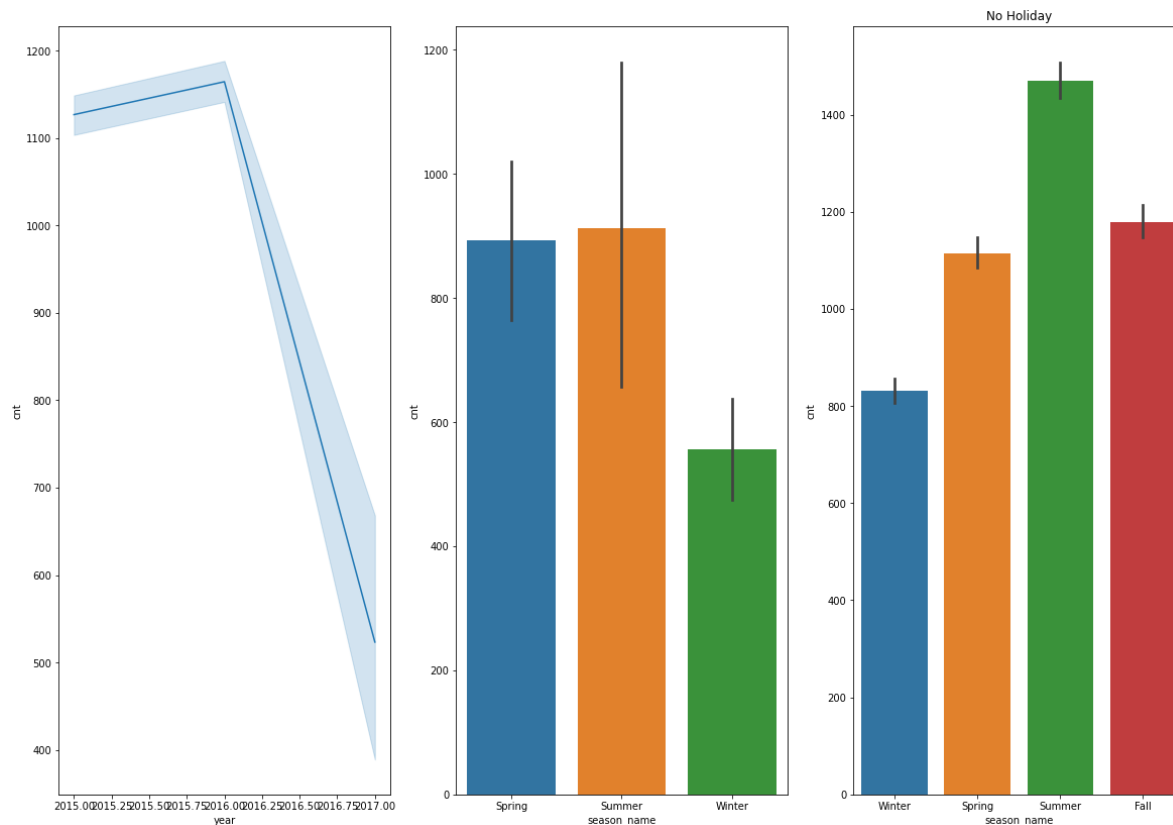
```

from turtle import title

fig, ax = plt.subplots(1,3, figsize = (20,14))

sns.lineplot(x = df.year , y = df.cnt , ax = ax[0]) ;
sns.barplot(x = df[df["is_holiday"] == 1]["season_name"] , y = df[df["is_holiday"] == 1].cnt
plt.title("No Holiday")
sns.barplot(x = df[df["is_holiday"] == 0]["season_name"] , y = df[df["is_holiday"] == 0].cnt

```



15. Visualize the distribution of bike shares by weekday/weekend with piechart and barplot

In [38]:

```
df.groupby("is_weekend").cnt.mean()
```

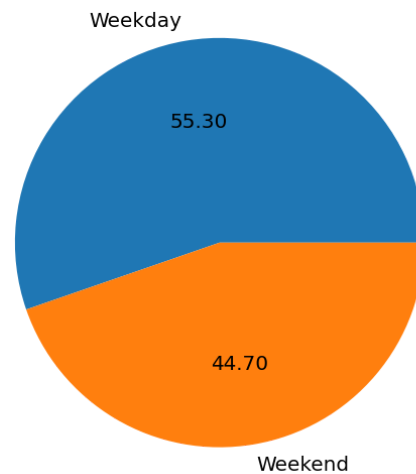
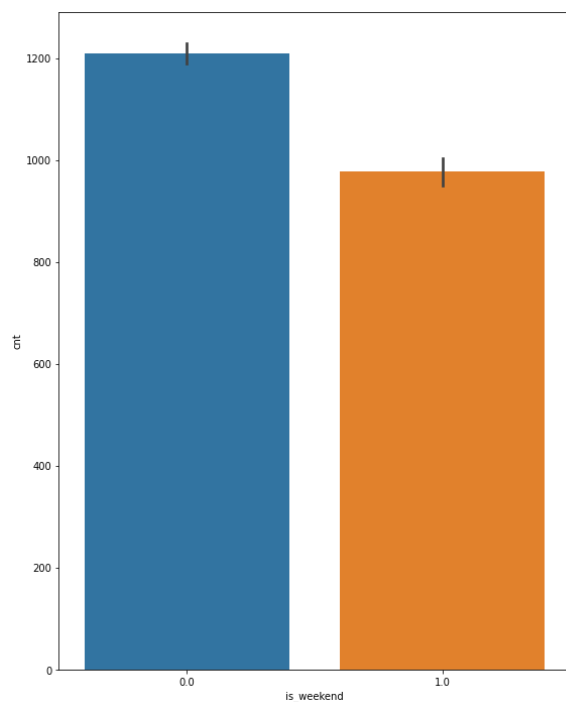
Out[38]:

```
is_weekend
0.0      1209.274831
1.0       977.415694
Name: cnt, dtype: float64
```

In [39]:

```
fig, ax = plt.subplots(1,2, figsize = (20,12))

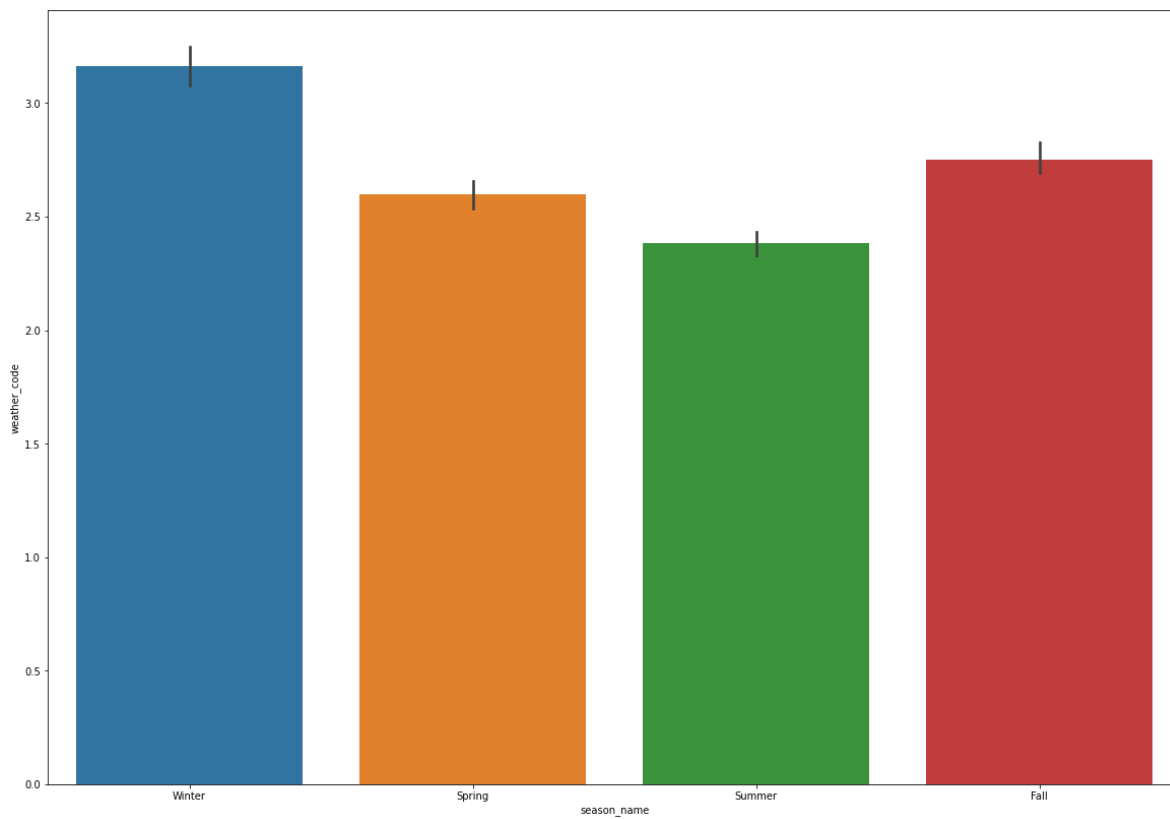
sns.barplot(x = df["is_weekend"] , y = df["cnt"] , ax = ax[0]);
plt.pie(x = df.groupby("is_weekend").cnt.mean(), labels = ["Weekday" , "Weekend"] , autopct
```



16. Plot the distribution of weather code by seasons

In [40]:

```
plt.figure(figsize=(20,14))  
sns.barplot(x = df["season_name"] , y = df.weather_code ) ;
```



In [41]:

Additional

```
df.weather_code_mapped = df.weather_code.map({
    1: 'Clear',
    2: 'Few clouds',
    3: 'Broken clouds',
    4: 'Cloudy',
    7: 'Light Rain shower',
    10: 'Thunderstorm',
    26: 'Snowfall',
    94: 'Freezing Fog'
})
```

C:\Users\Emincan\AppData\Local\Temp\ipykernel_15924\3093734476.py:3: UserWarning: Pandas doesn't allow columns to be created via a new attribute name - see <https://pandas.pydata.org/pandas-docs/stable/indexing.html#attribute-access> (<https://pandas.pydata.org/pandas-docs/stable/indexing.html#attribute-access>)

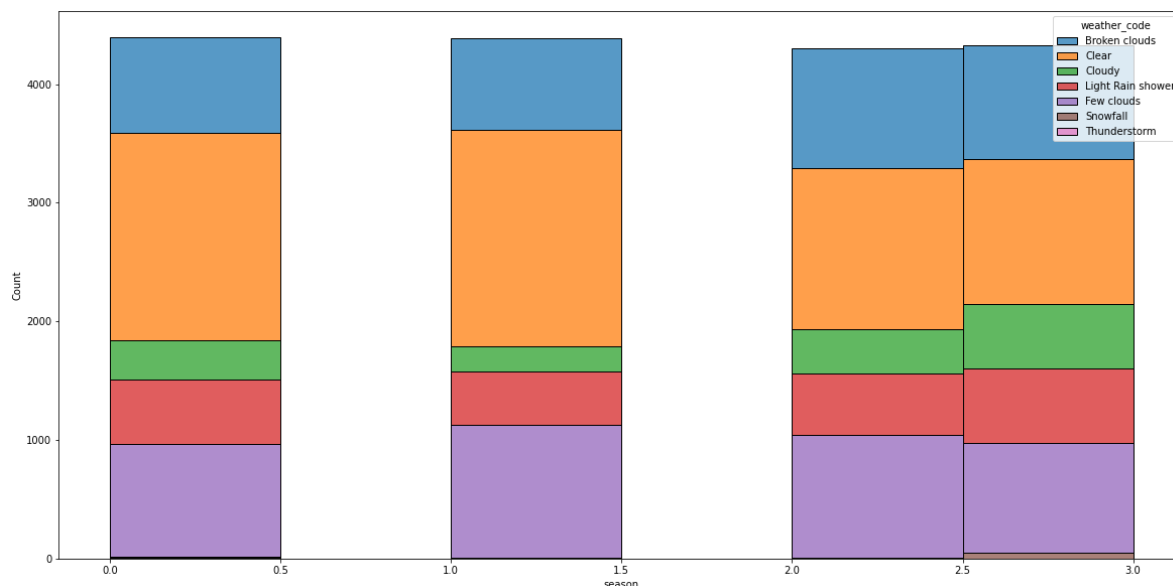
```
df.weather_code_mapped = df.weather_code.map({
```

In [42]:

Additional

```
plt.figure(figsize=(20, 10))
```

```
sns.histplot(binwidth=0.5, x=df.season, hue=df.weather_code_mapped, data=df, stat="count",
```



Conclusions

There was totally clear data. No null and no duplicate rows.

Too many days weather is clear. Freezing Fog never happened. Snowfall sometimes happened. Rain with thunderstorms happened the least.

As we expect the spring and summer have too many clear days. In the fall and winter have got more Scattered and Broken clouds.

Bike shares have positive relations with Temperature, Feeling Temperature, Hour and Wind Speed.

Bike shares have negative relations with humidity, weather status and season.

As a normally too strong positive correlation between temperature and feeling temperature.

As a normally positive correlation between Temperature/Feeling Temperature and months.

As a normally , positive correlation between the hum and seasons.

Humidity and weather status have positive realations.

Humidity and wind speed have negative realations.

Bike shares is declining but peaked in the summer of 2015

As a normally , In summers more bike shares happens.

In all seasons. Early 8-9a.m and 17-18p.m too many bikes shares.

In weekdays also same eary 8-9a.m and 17.18p.m.

But in the weekends too many bikes shares around at 14-15p.m and have normal distribution.

On a holiday, less bike is shared than normal.

In a normal day(not holiday) summer have too many bike shares. Winter have lest.

During the holidays, not happened any bike shares in Fall. (This is strange) Winter still lest. Summer and spring almost the same bike shares.

Seasons have normal weather status. Hard to beautiful ==> Winter>Fall>Spring>Summer

That's all.

Thanks for Attending!..



