CASE -

- We are going to find the total count of the vehicle for particular day.

Data Set Information:

- Bike sharing systems are new generation of traditional bike rentals where whole process from membership, rental and return back has become automatic. Through these systems, user is able to easily rent a bike from a particular position and return back at another position. Currently, there are about over 500 bike-sharing programs around the world which is composed of over 500 thousands bicycles. Today, there exists great interest in these systems due to their important role in traffic, environmental and health issues.
- Apart from interesting real world applications of bike sharing systems, the characteristics of data being generated by these systems make them attractive for the research. Opposed to other transport services such as bus or subway, the duration of travel, departure and arrival position is explicitly recorded in these systems. This feature turns bike sharing system into a virtual sensor network that can be used for sensing mobility in the city. Hence, it is expected that most of important events in the city could be detected via monitoring these data.

Attribute Information: ¶

Both hour.csv and day.csv have the following fields, except hr which is not available in day.csv

- instant: record index
- dteday : date
- season : season (1:winter, 2:spring, 3:summer, 4:fall)
- yr : year (0: 2011, 1:2012)
- mnth : month (1 to 12)
- hr : hour (0 to 23)
- holiday : weather day is holiday or not (extracted from [Web Link])
- weekday : day of the week
- workingday : if day is neither weekend nor holiday is 1, otherwise is 0.
- weathersit :
- 1: Clear, Few clouds, Partly cloudy, Partly cloudy
- 2: Mist + Cloudy, Mist + Broken clouds, Mist + Few clouds, Mist
- 3: Light Snow, Light Rain + Thunderstorm + Scattered clouds, Light Rain + Scattered clouds
- 4: Heavy Rain + Ice Pallets + Thunderstorm + Mist, Snow + Fog
- temp : Normalized temperature in Celsius. The values are derived via (t-t_min)/(t_max-t_min), t_min=-8, t_max=+39 (only in hourly scale)
- atemp: Normalized feeling temperature in Celsius. The values are derived via (t-t_min)/(t_max-t_min), t_min=-16, t_max=+50 (only in hourly scale)
- hum: Normalized humidity. The values are divided to 100 (max)
- windspeed: Normalized wind speed. The values are divided to 67 (max)

- casual: count of casual users
- registered: count of registered users
- cnt: count of total rental bikes including both casual and registered

Importing the Required libraries

In [1]:
```
## Importing the Libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
%matplotlib inline
warnings.filterwarnings('ignore')
pd.options.display.max_columns = 999
```

Loading the dataset

In [2]:
```
df = pd.read_csv(r"C:\Users\lenovo\Desktop\hour.csv")
df.head()
```

Out[2]:

	instant	dteday	season	yr	mnth	hr	holiday	weekday	workingday	weathersit	temp	ater
0	1	2011-01-01	1	0	1	0	0	6	0	1	0.24	0.28
1	2	2011-01-01	1	0	1	1	0	6	0	1	0.22	0.27
2	3	2011-01-01	1	0	1	2	0	6	0	1	0.22	0.27
3	4	2011-01-01	1	0	1	3	0	6	0	1	0.24	0.28
4	5	2011-01-01	1	0	1	4	0	6	0	1	0.24	0.28

In [3]:
```
# statistical info

df.describe()
```

Out[3]:

	instant	season	yr	mnth	hr	holiday	
count	17379.0000	17379.000000	17379.000000	17379.000000	17379.000000	17379.000000	1737
mean	8690.0000	2.501640	0.502561	6.537775	11.546752	0.028770	
std	5017.0295	1.106918	0.500008	3.438776	6.914405	0.167165	
min	1.0000	1.000000	0.000000	1.000000	0.000000	0.000000	
25%	4345.5000	2.000000	0.000000	4.000000	6.000000	0.000000	
50%	8690.0000	3.000000	1.000000	7.000000	12.000000	0.000000	
75%	13034.5000	3.000000	1.000000	10.000000	18.000000	0.000000	
max	17379.0000	4.000000	1.000000	12.000000	23.000000	1.000000	

In [4]:
```
# datatype info

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 17379 entries, 0 to 17378
Data columns (total 17 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   instant     17379 non-null  int64  
 1   dteday      17379 non-null  object 
 2   season      17379 non-null  int64  
 3   yr          17379 non-null  int64  
 4   mnth        17379 non-null  int64  
 5   hr          17379 non-null  int64  
 6   holiday     17379 non-null  int64  
 7   weekday     17379 non-null  int64  
 8   workingday  17379 non-null  int64  
 9   weathersit  17379 non-null  int64  
 10  temp        17379 non-null  float64
 11  atemp       17379 non-null  float64
 12  hum         17379 non-null  float64
 13  windspeed   17379 non-null  float64
 14  casual      17379 non-null  int64  
 15  registered  17379 non-null  int64  
 16  cnt         17379 non-null  int64  
dtypes: float64(4), int64(12), object(1)
memory usage: 2.3+ MB
```

In [5]:
```
# unique values

df.apply(lambda x: len(x.unique()))
```

Out[5]:
```
instant       17379
dteday          731
season            4
yr                2
mnth             12
hr               24
holiday           2
weekday           7
workingday        2
weathersit        4
temp             50
atemp            65
hum              89
windspeed        30
casual          322
registered      776
cnt             869
dtype: int64
```

Preprocessing the dataset

In [6]:
```
# check for null values

df.isnull().sum()
```

Out[6]:
```
instant       0
dteday        0
season        0
yr            0
mnth          0
hr            0
holiday       0
weekday       0
workingday    0
weathersit    0
temp          0
atemp         0
hum           0
windspeed     0
casual        0
registered    0
cnt           0
dtype: int64
```

In [7]:
```
# renaming the columns into proper names

df = df.rename(columns={'weathersit':'weather',
                        'yr':'year',
                        'mnth':'month',
                        'hr':'hour',
                        'hum':'humidity',
                        'cnt':'count'})
df.head()
```

Out[7]:

	instant	dteday	season	year	month	hour	holiday	weekday	workingday	weather	temp
0	1	2011-01-01	1	0	1	0	0	6	0	1	0.24
1	2	2011-01-01	1	0	1	1	0	6	0	1	0.22
2	3	2011-01-01	1	0	1	2	0	6	0	1	0.22
3	4	2011-01-01	1	0	1	3	0	6	0	1	0.24
4	5	2011-01-01	1	0	1	4	0	6	0	1	0.24

In [8]:
```
# dropping unwanted columns

df = df.drop(columns=['instant', 'dteday', 'year'])
```

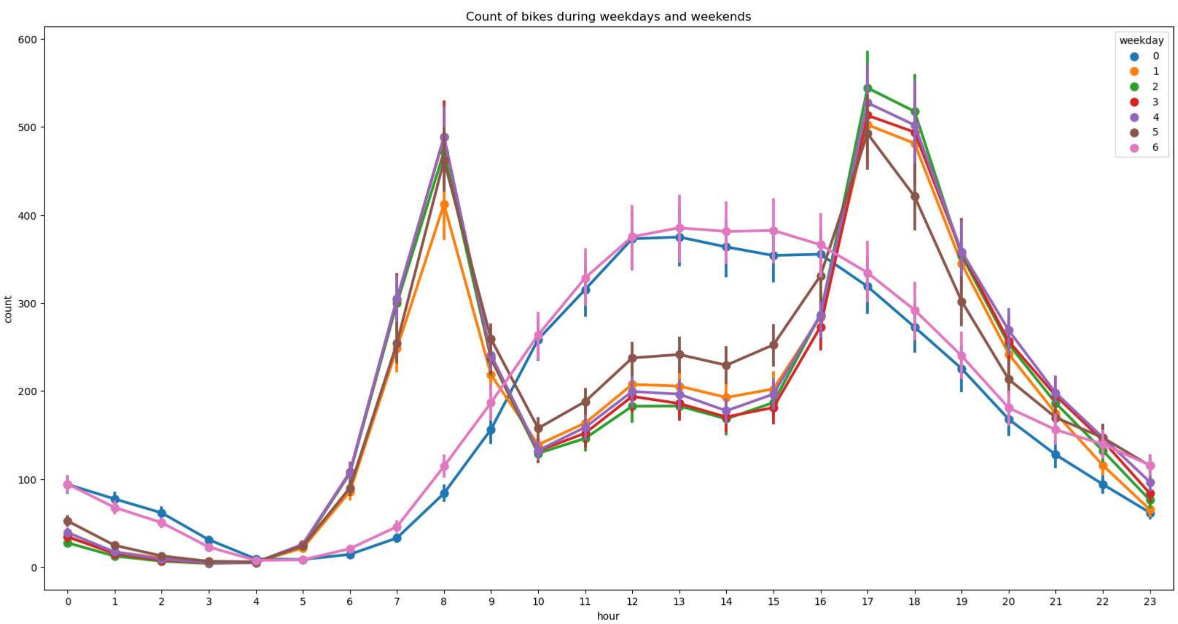
In [9]:
```
# change int columns to category

cols = ['season','month','hour','holiday','weekday','workingday','weather']

for col in cols:
    df[col] = df[col].astype('category')
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 17379 entries, 0 to 17378
Data columns (total 14 columns):
 #   Column      Non-Null Count  Dtype   
---  ------      --------------  -----   
 0   season      17379 non-null  category
 1   month       17379 non-null  category
 2   hour        17379 non-null  category
 3   holiday     17379 non-null  category
 4   weekday     17379 non-null  category
 5   workingday  17379 non-null  category
 6   weather     17379 non-null  category
 7   temp        17379 non-null  float64 
 8   atemp       17379 non-null  float64 
 9   humidity    17379 non-null  float64 
 10  windspeed   17379 non-null  float64 
 11  casual      17379 non-null  int64   
 12  registered  17379 non-null  int64   
 13  count       17379 non-null  int64   
dtypes: category(7), float64(4), int64(3)
memory usage: 1.0 MB
```

Exploratory Data Analysis

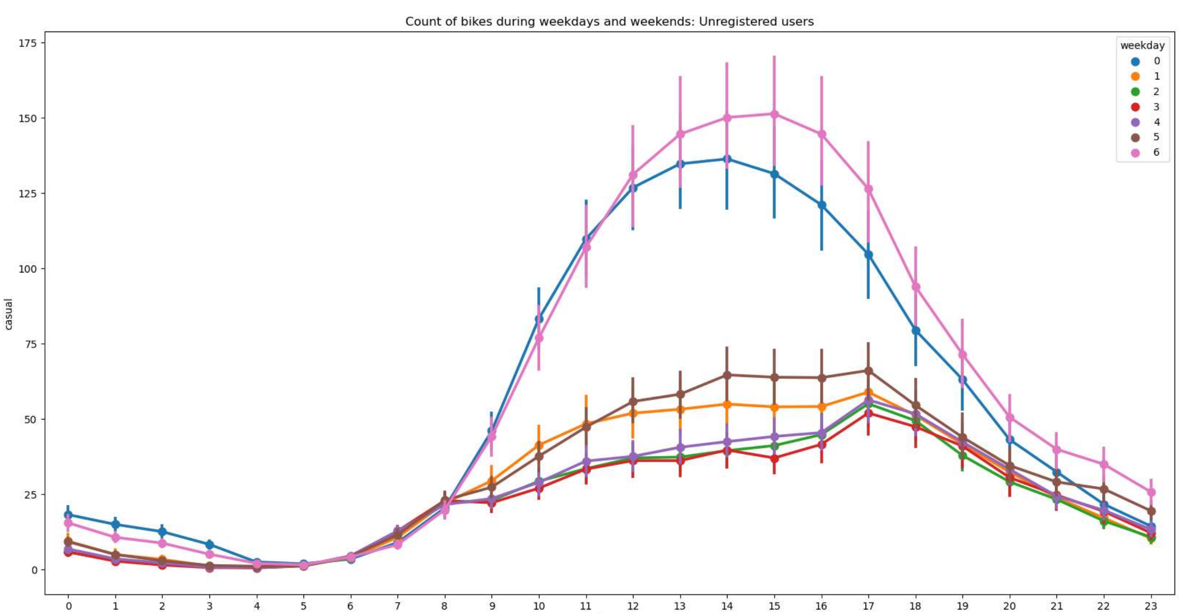
In [10]:
```
fig, ax = plt.subplots(figsize=(20,10))
sns.pointplot(data=df, x='hour', y='count', hue='weekday', ax=ax)
ax.set(title='Count of bikes during weekdays and weekends')
```

Out[10]:
```
[Text(0.5, 1.0, 'Count of bikes during weekdays and weekends')]
```



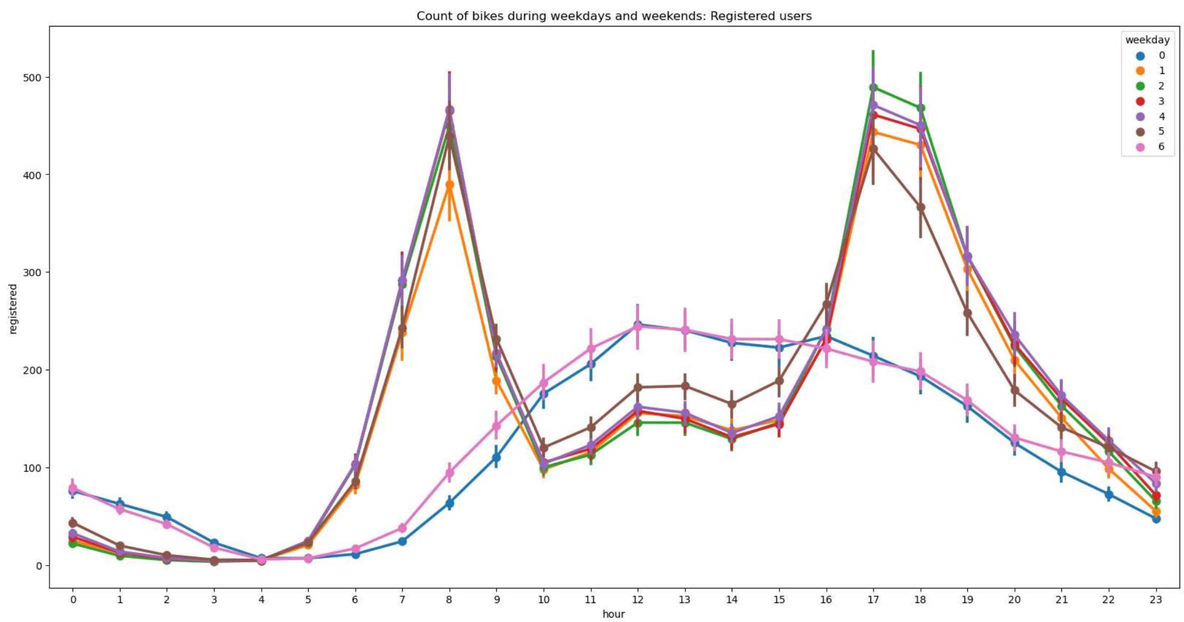
In [11]:
```
fig, ax = plt.subplots(figsize=(20,10))
sns.pointplot(data=df, x='hour', y='casual', hue='weekday', ax=ax)
ax.set(title='Count of bikes during weekdays and weekends: Unregistered users'
```

Out[11]:
```
[Text(0.5, 1.0, 'Count of bikes during weekdays and weekends: Unregistered u
sers')]
```



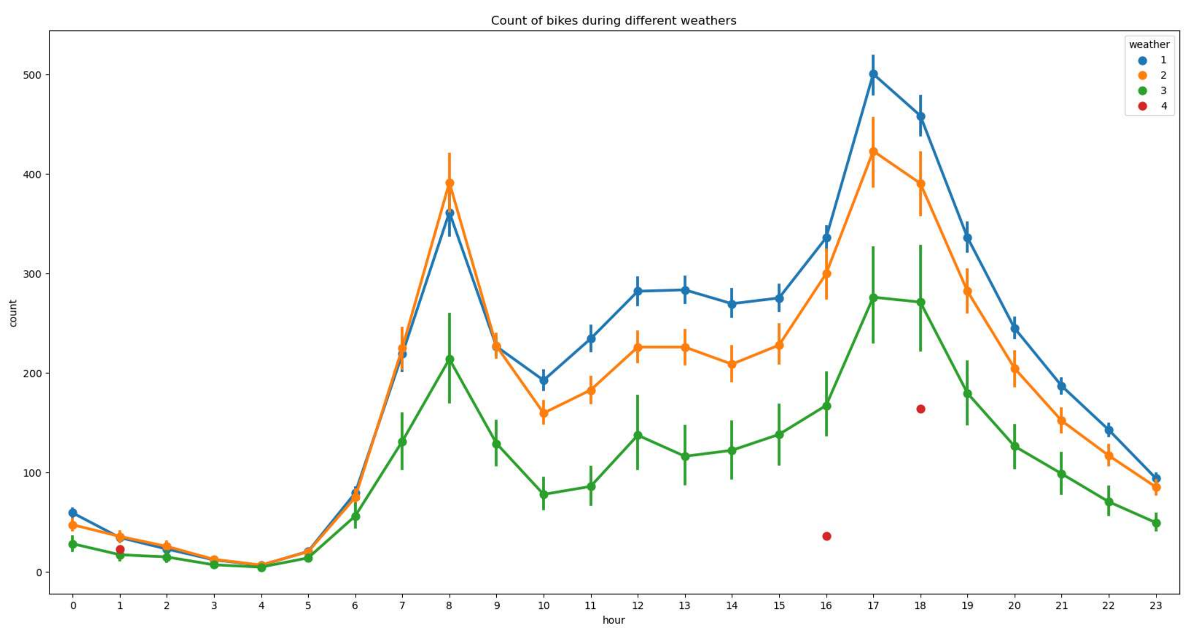
In [12]:
```
fig, ax = plt.subplots(figsize=(20,10))
sns.pointplot(data=df, x='hour', y='registered', hue='weekday', ax=ax)
ax.set(title='Count of bikes during weekdays and weekends: Registered users')
```

Out[12]:
```
[Text(0.5, 1.0, 'Count of bikes during weekdays and weekends: Registered use
rs')]
```



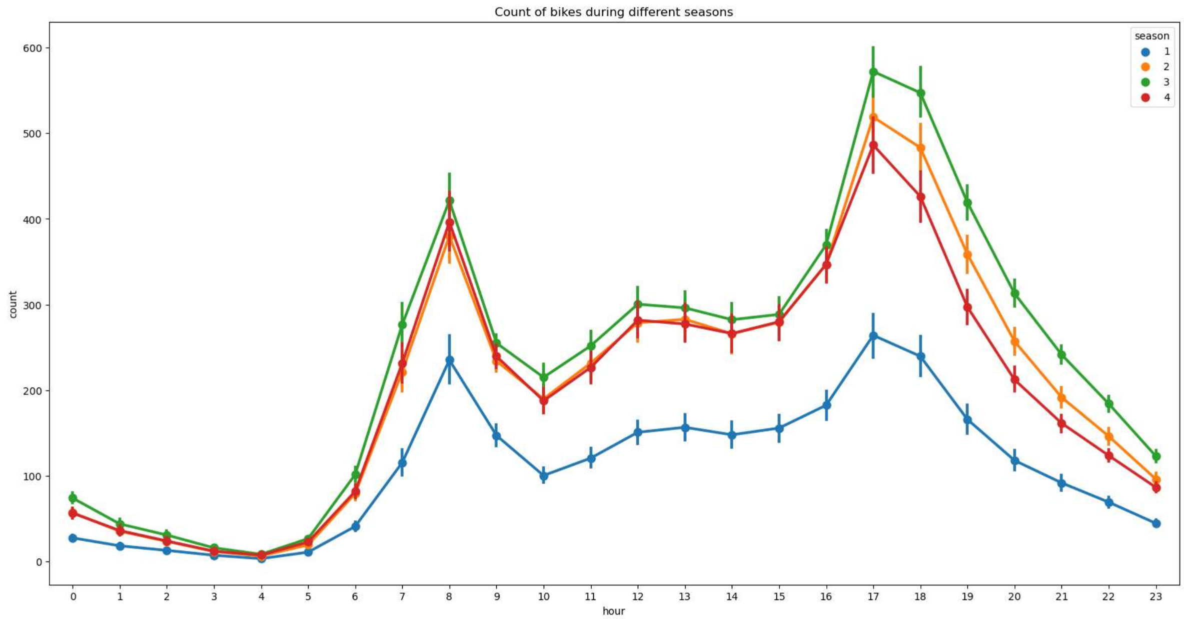
In [13]:
```
fig, ax = plt.subplots(figsize=(20,10))
sns.pointplot(data=df, x='hour', y='count', hue='weather', ax=ax)
ax.set(title='Count of bikes during different weathers')
```

Out[13]:
```
[Text(0.5, 1.0, 'Count of bikes during different weathers')]
```



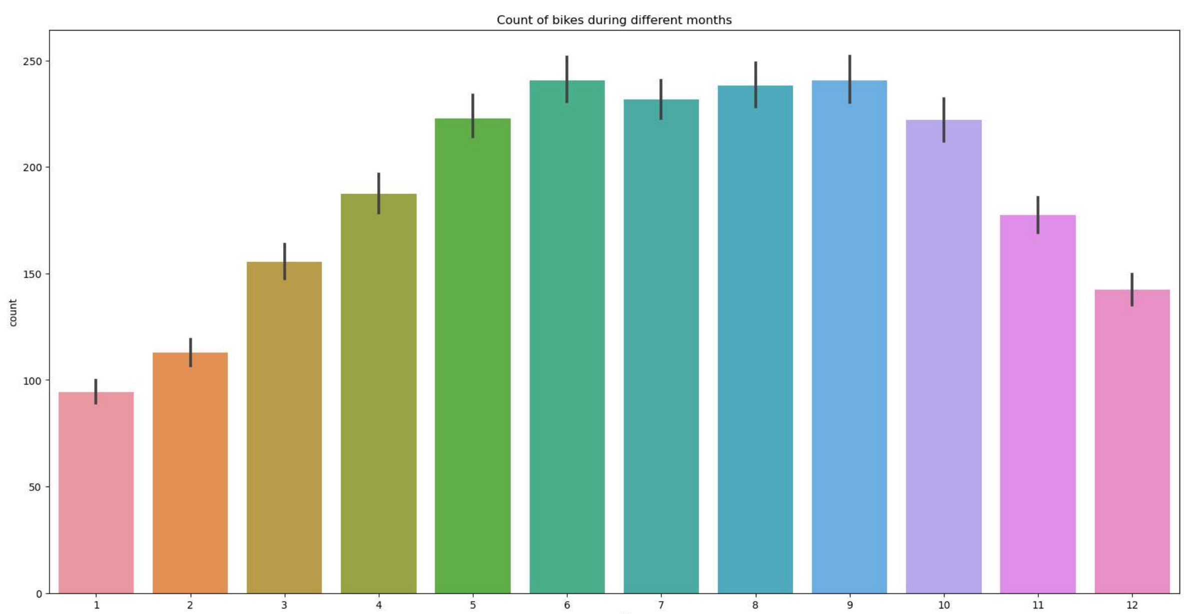
In [14]:
```
fig, ax = plt.subplots(figsize=(20,10))
sns.pointplot(data=df, x='hour', y='count', hue='season', ax=ax)
ax.set(title='Count of bikes during different seasons')
```

Out[14]: [Text(0.5, 1.0, 'Count of bikes during different seasons')]



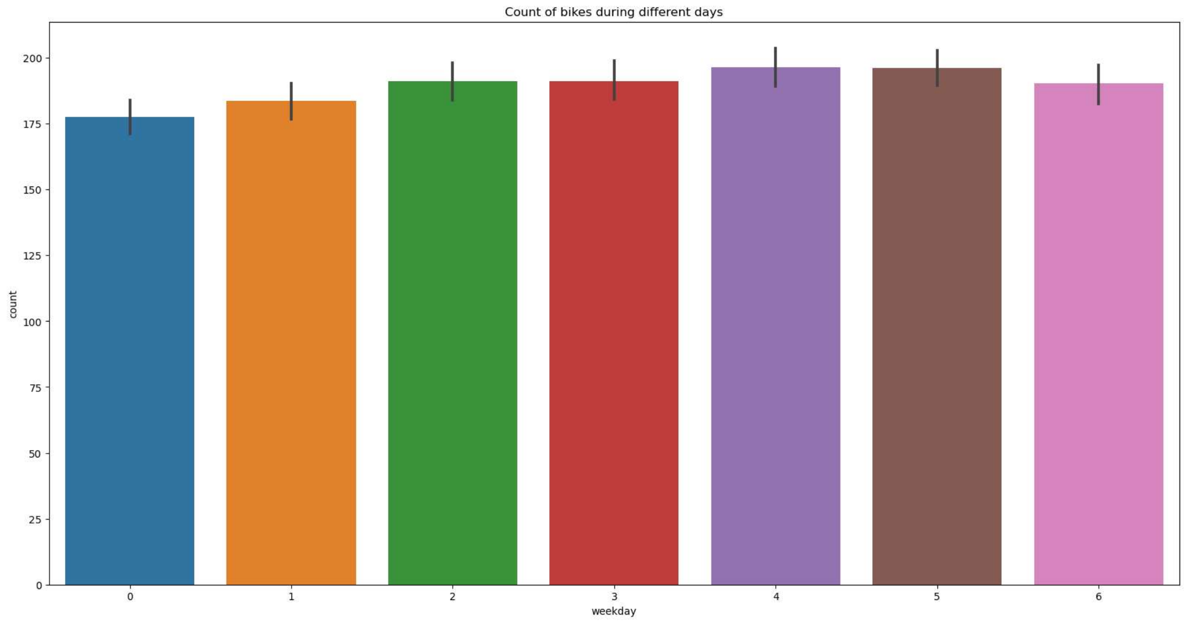
In [15]:
```
fig, ax = plt.subplots(figsize=(20,10))
sns.barplot(data=df, x='month', y='count', ax=ax)
ax.set(title='Count of bikes during different months')
```

Out[15]: [Text(0.5, 1.0, 'Count of bikes during different months')]



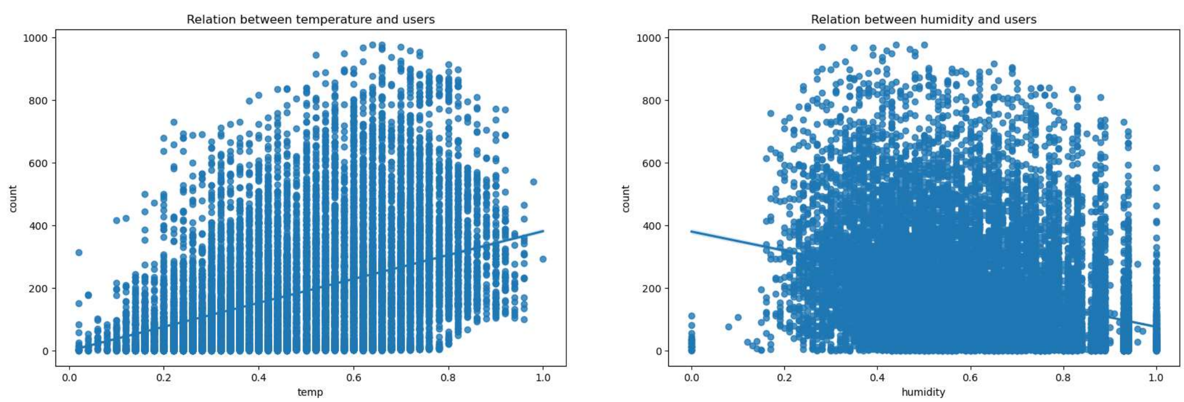
In [16]:
```
fig, ax = plt.subplots(figsize=(20,10))
sns.barplot(data=df, x='weekday', y='count', ax=ax)
ax.set(title='Count of bikes during different days')
```

Out[16]:
```
[Text(0.5, 1.0, 'Count of bikes during different days')]
```



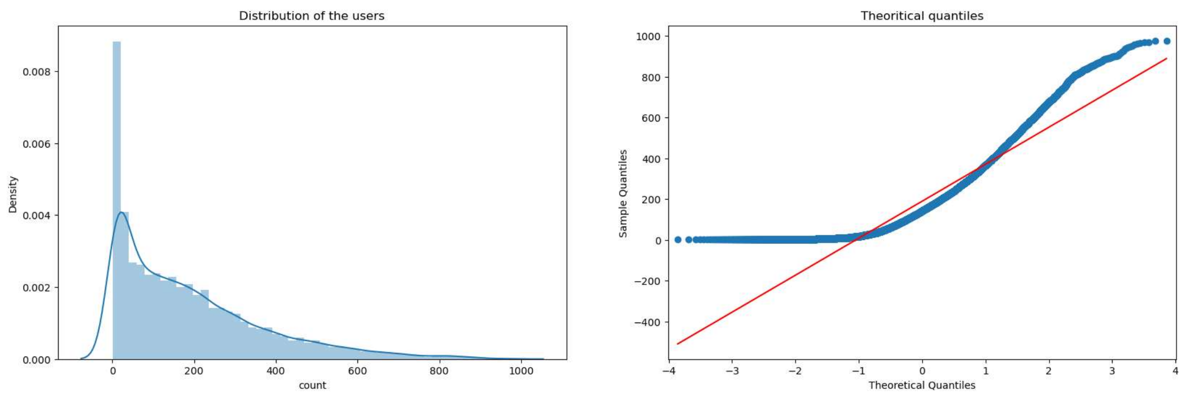
In [17]:
```
fig, (ax1,ax2) = plt.subplots(ncols=2, figsize=(20,6))
sns.regplot(x=df['temp'], y=df['count'], ax=ax1)
ax1.set(title="Relation between temperature and users")
sns.regplot(x=df['humidity'], y=df['count'], ax=ax2)
ax2.set(title="Relation between humidity and users")
```

Out[17]:
```
[Text(0.5, 1.0, 'Relation between humidity and users')]
```



In [18]:
```
from statsmodels.graphics.gofplots import qqplot
fig, (ax1,ax2) = plt.subplots(ncols=2, figsize=(20,6))
sns.distplot(df['count'], ax=ax1)
ax1.set(title='Distribution of the users')
qqplot(df['count'], ax=ax2, line='s')
ax2.set(title='Theoritical quantiles')
```

Out[18]:
```
[Text(0.5, 1.0, 'Theoritical quantiles')]
```



In [19]:
```
# transforming the data

df['count'] = np.log(df['count'])
```

In [20]:
```
corr = df.corr()
plt.figure(figsize=(15,10))
sns.heatmap(corr, annot=True, annot_kws={'size':15})
```

Out[20]: <AxesSubplot:>

One Hot Encoding

In [21]:
```
pd.get_dummies(df['season'], prefix='season', drop_first=True)
```

Out[21]:

	season_2	season_3	season_4
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0
...	...	...	...
17374	0	0	0
17375	0	0	0
17376	0	0	0
17377	0	0	0
17378	0	0	0

17379 rows × 3 columns

In [22]:
```
df_oh = df

def one_hot_encoding(data, column):
    data = pd.concat([data, pd.get_dummies(data[column], prefix=column, drop_f
    data = data.drop([column], axis=1)
    return data

cols = ['season','month','hour','holiday','weekday','workingday','weather']

for col in cols:
    df_oh = one_hot_encoding(df_oh, col)
df_oh.head()
```

Out[22]:

	temp	atemp	humidity	windspeed	casual	registered	count	season_2	season_3	seaso
0	0.24	0.2879	0.81	0.0	3	13	2.772589	0	0	
1	0.22	0.2727	0.80	0.0	8	32	3.688879	0	0	
2	0.22	0.2727	0.80	0.0	5	27	3.465736	0	0	
3	0.24	0.2879	0.75	0.0	3	10	2.564949	0	0	
4	0.24	0.2879	0.75	0.0	0	1	0.000000	0	0	

Input Split

In [23]:
```
X = df_oh.drop(columns=['atemp', 'windspeed', 'casual', 'registered', 'count']
y = df_oh['count']
```

Model Training

In [24]:
```
from sklearn.linear_model import LinearRegression, Ridge, HuberRegressor, Elas
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor,

models = [LinearRegression(),
          Ridge(),
          HuberRegressor(),
          ElasticNetCV(),
          DecisionTreeRegressor(),
          RandomForestRegressor(),
          ExtraTreesRegressor(),
          GradientBoostingRegressor()]
```

In [25]:
```
from sklearn import model_selection
def train(model):
    kfold = model_selection.KFold(n_splits=5)
    pred = model_selection.cross_val_score(model, X, y, cv=kfold, scoring='neg
    cv_score = pred.mean()
    print('Model:',model)
    print('CV score:', abs(cv_score))
```

In [26]:
```
# Error matric, lesser the error, better the model

for model in models:
    train(model)
```

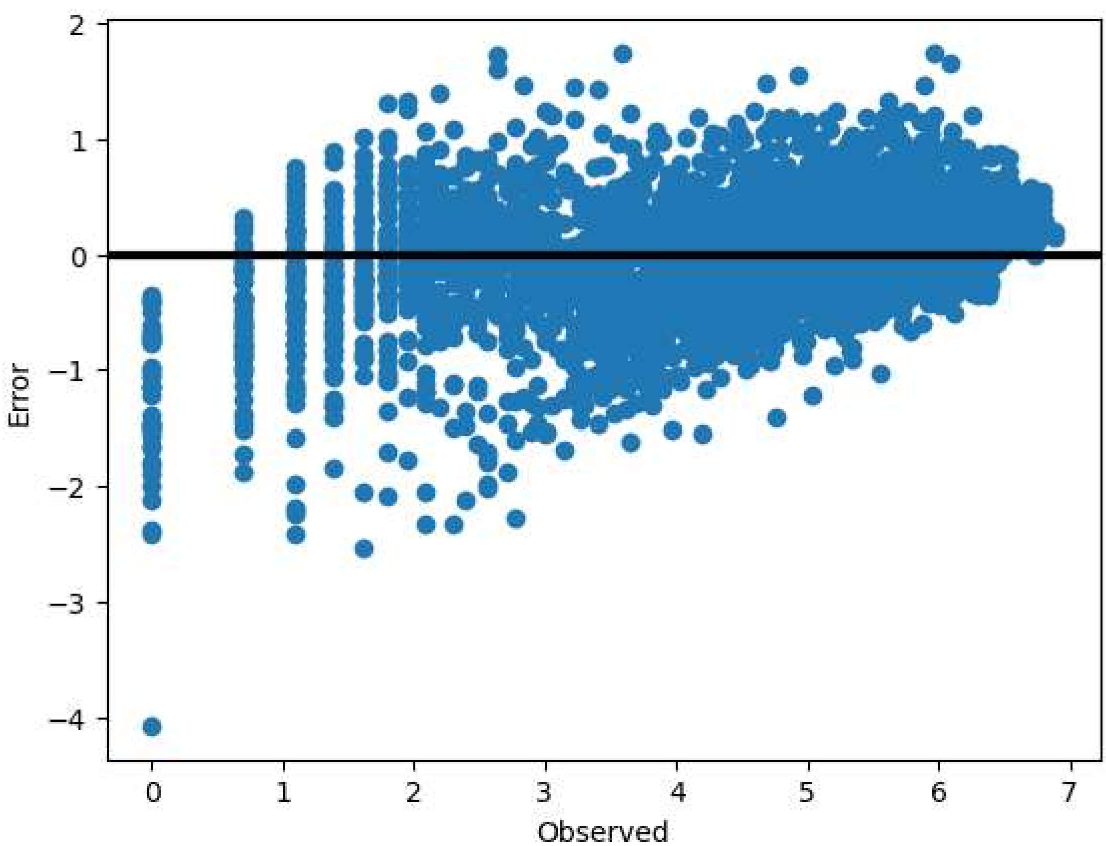
```
Model: LinearRegression()
CV score: 0.6313095891251297
Model: Ridge()
CV score: 0.6304079414191442
Model: HuberRegressor()
CV score: 0.6603303925176032
Model: ElasticNetCV()
CV score: 0.6252222784219456
Model: DecisionTreeRegressor()
CV score: 0.6077044029703076
Model: RandomForestRegressor()
CV score: 0.3895245689760533
Model: ExtraTreesRegressor()
CV score: 0.4050847971258724
Model: GradientBoostingRegressor()
CV score: 0.4714300371061174
```

Train Test Split

In [27]:
```
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(X, y, test_size=0.25, ranc
```

In [28]:
```
model = RandomForestRegressor()
model.fit(x_train, y_train)
y_pred = model.predict(x_test)
```

In [29]:
```
# plot the error difference

error = y_test - y_pred
fig, ax = plt.subplots()
ax.scatter(y_test, error)
ax.axhline(lw=3, color='black')
ax.set_xlabel('Observed')
ax.set_ylabel('Error')
plt.show()
```



In [30]:
```
# Root mean square error of model

from sklearn.metrics import mean_squared_error
np.sqrt(mean_squared_error(y_test, y_pred))
```

Out[30]: 0.48603764342900596

Final Conclusion

- Out of the 8 models, Random Forest Regressor is the top performer with the least cv score.
- You may do various analysis with the variety of results given from the different models used.
- You can also use hyperparameter tuning to improve the model performance.

- - - - - - - - X X X X X X X X - - - - - - - -