In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

```
/usr/local/lib/python3.6/dist-packages/statsmodels/tools/_testing.py:19: FutureWarning: p
andas.util.testing is deprecated. Use the functions in the public API at pandas.testing i
nstead.
  import pandas.util.testing as tm
```

In [2]:

```
df = pd.read_csv('train_bikes.csv', parse_dates = ['datetime'])
```

The total count of bikes rented during each hour covered by the test set, using only information available prior to the rental period.

In [3]:

```
df.head()
```

Out[3]:

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual	registered	count
0	2011-01-01 00:00:00	1	0	0	1	9.84	14.395	81	0.0	3	13	16
1	2011-01-01 01:00:00	1	0	0	1	9.02	13.635	80	0.0	8	32	40
2	2011-01-01 02:00:00	1	0	0	1	9.02	13.635	80	0.0	5	27	32
3	2011-01-01 03:00:00	1	0	0	1	9.84	14.395	75	0.0	3	10	13
4	2011-01-01 04:00:00	1	0	0	1	9.84	14.395	75	0.0	0	1	1

In [4]:

```
df.dtypes
```

Out[4]:

```
datetime      datetime64[ns]
season                 int64
holiday                int64
workingday             int64
weather                int64
temp                 float64
atemp                float64
humidity               int64
windspeed            float64
casual                 int64
registered             int64
count                  int64
dtype: object
```

Checking for any missing values

In [5]:

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

Out[5]:

```
datetime      0
season        0
holiday       0
workingday    0
weather       0
temp          0
atemp         0
humidity      0
windspeed     0
casual        0
registered    0
count         0
dtype: int64
```

In [6]:

```
# Minimum value for each column
df.min()
```

Out[6]:

```
datetime      2011-01-01 00:00:00
season                          1
holiday                         0
workingday                      0
weather                         1
temp                         0.82
atemp                        0.76
humidity                        0
windspeed                       0
casual                          0
registered                      0
count                           1
dtype: object
```

Splittine datetime into Day, Month, hour

In [7]:

```
df['Day'] = df['datetime'].dt.day
df['Month'] = df['datetime'].dt.month
df['Hour'] = df['datetime'].dt.hour
#df['Journey_year'] = df['Date_of_Journey'].dt.year
df.drop(['datetime'], axis = 1, inplace=True)
```

In [8]:

```
df.head()
```

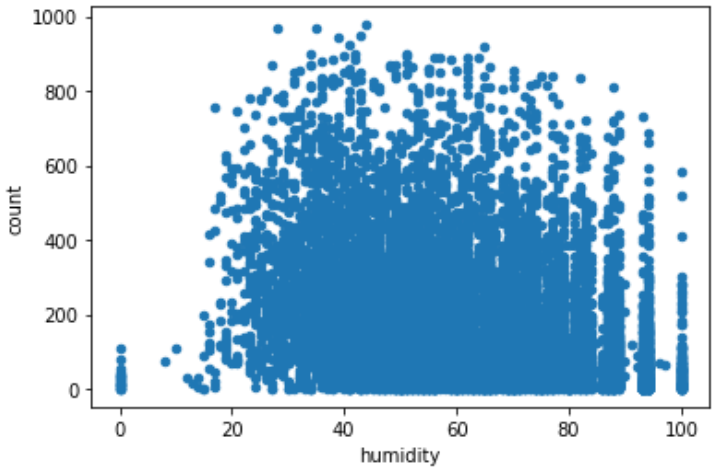
Out[8]:

	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual	registered	count	Day	Month	Hour
0	1	0	0	1	9.84	14.395	81	0.0	3	13	16	1	1	0
1	1	0	0	1	9.02	13.635	80	0.0	8	32	40	1	1	1
2	1	0	0	1	9.02	13.635	80	0.0	5	27	32	1	1	2
3	1	0	0	1	9.84	14.395	75	0.0	3	10	13	1	1	3
4	1	0	0	1	9.84	14.395	75	0.0	0	1	1	1	1	4

Analysis of count based on Humidity and windspeed

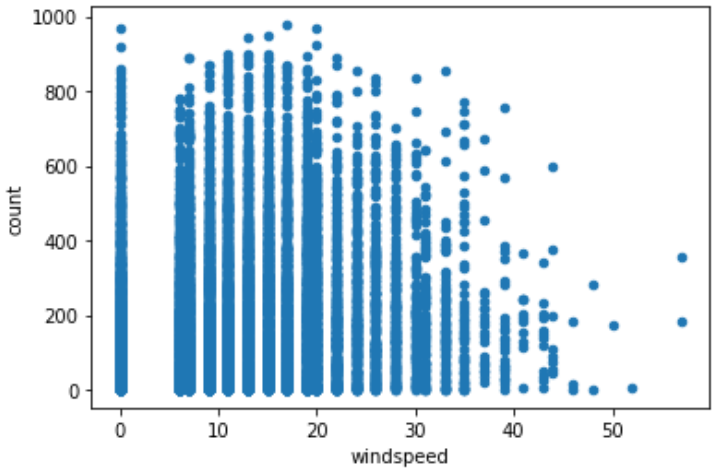
In [9]:

```
df.plot.scatter('humidity', 'count')
plt.show()
```



In [10]:

```
df.plot.scatter('windspeed', 'count')
plt.show()
```



From the above scatter plots, we can analysis following things.

1. **The distribution of humidity is more between 20-80.**
2. **Count reaches maximum for these ranges. Whereas for humidity 0 and 100, count max is around 200 and 600.**
3. **The count is max for almost all wind speed expect for high wind speeds.**

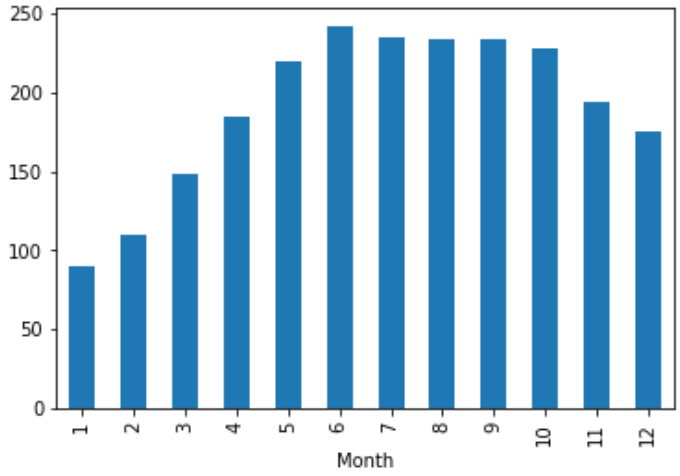
Count based on day and month

In [11]:

```
data2 = df.groupby('Month')['count'].mean()
print(data2)
data2.plot.bar()
plt.show()
```

```
Month
1       90.366516
2      110.003330
3      148.169811
4      184.160616
5      219.459430
6      242.031798
7      235.325658
8      234.118421
9      233.805281
10     227.699232
11     193.677278
```

```
12     175.614035
Name: count, dtype: float64
```

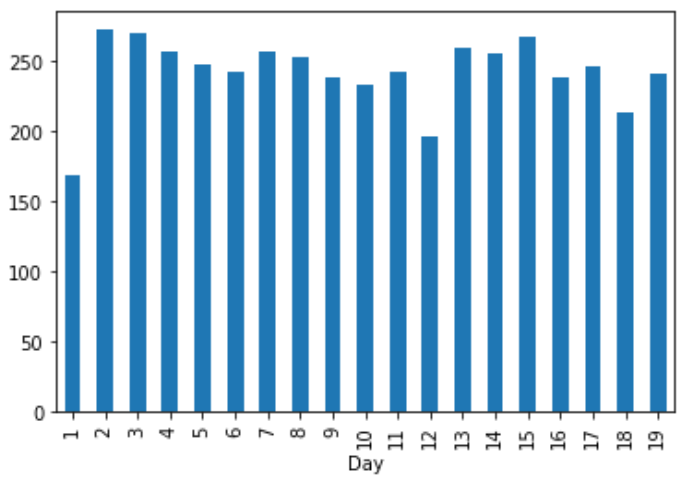


We can see that for the month of June, the count is maximum with a value of 242. Lets explore the count on June month.

In [12]:

```
data_june = df[df['Month'] == 6]
day = data_june.groupby('Day')['count'].mean()
print(day)
day.plot.bar()
plt.show()
```

```
Day
1      168.770833
2      272.666667
3      269.854167
4      257.083333
5      248.062500
6      241.729167
7      256.812500
8      252.854167
9      237.770833
10     233.000000
11     242.291667
12     196.500000
13     259.187500
14     255.291667
15     267.604167
16     238.937500
17     246.291667
18     212.875000
19     241.020833
Name: count, dtype: float64
```

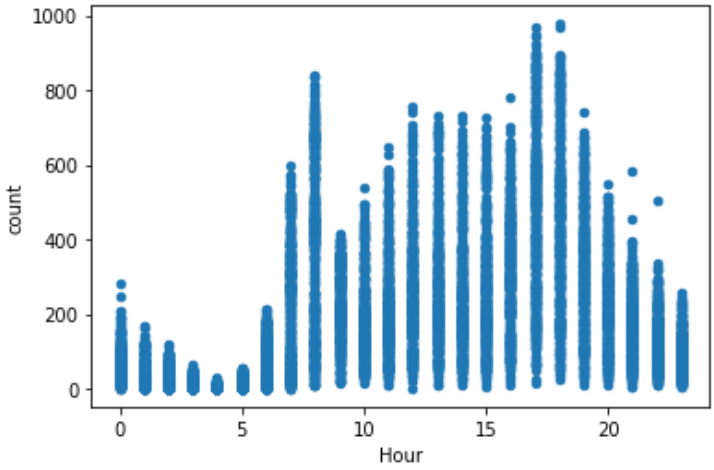


We can see that for June month, the count is max for 2nd day.

Count based on each hour

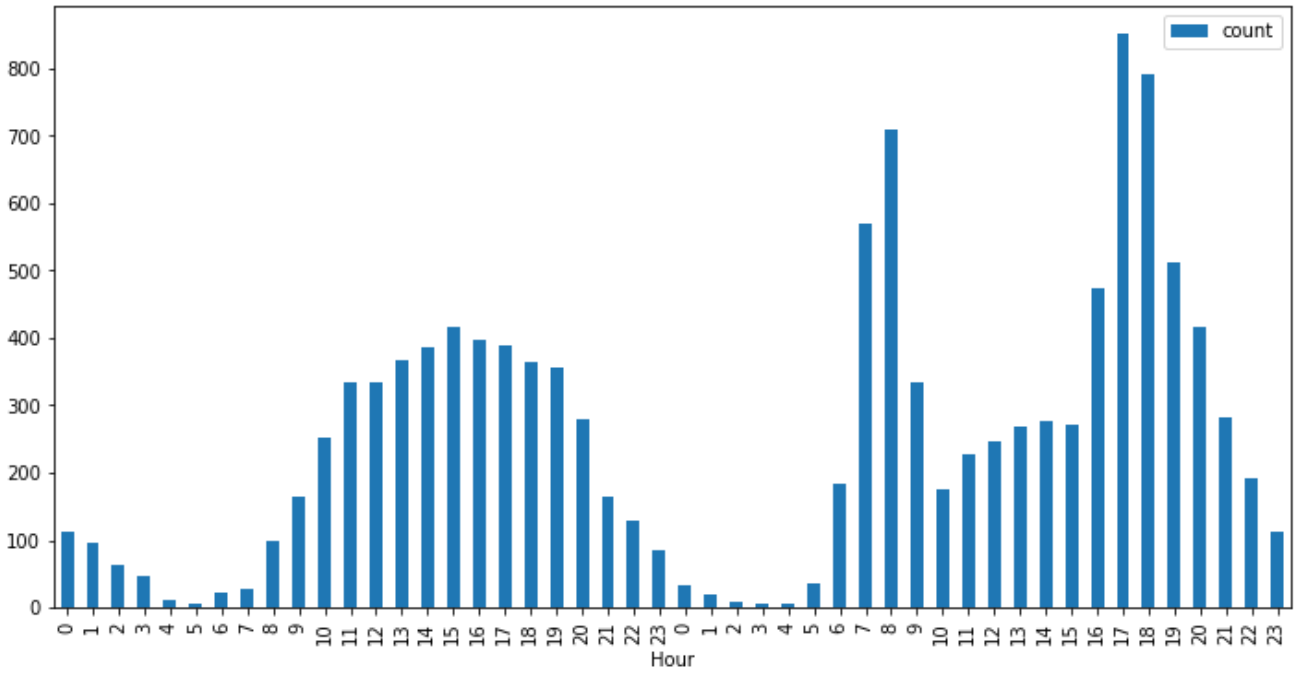
In [13]:

```
data4 = df.groupby('Hour')['count'].mean()
df.plot.scatter('Hour', 'count')
plt.show()
```



In [14]:

```
data = df[(df['Month']==6) & (df['Day']==5)]
data.plot.bar('Hour', 'count', figsize = (12, 6))
plt.show()
```

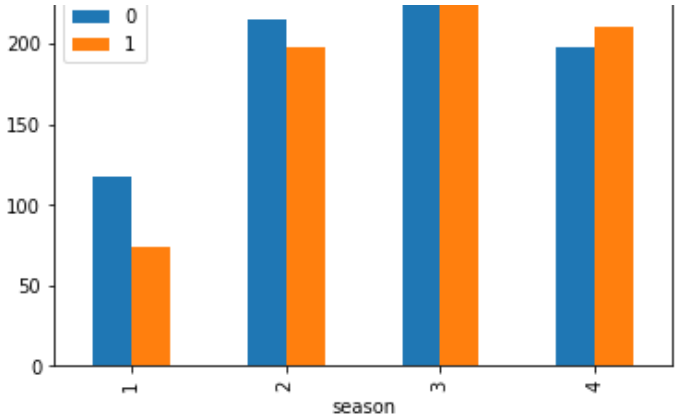


The bar plot shows the filtered data for June 5th. On June 5th, we can see that on 17:00 clock, max amount of cycles have been rented.

Count based on season and holiday

In [15]:

```
data3 = df.groupby(['season', 'holiday'])['count'].mean()
data3.unstack().plot.bar()
plt.show()
```



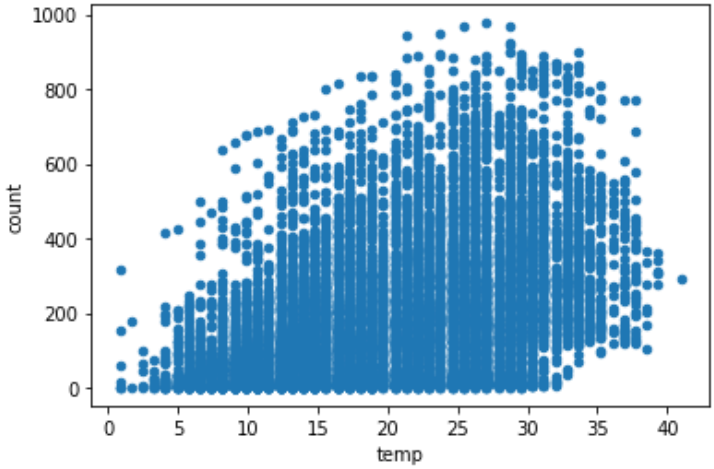
the above bar plot is distinguished between sesons and count. For each season, holiday or not is present.

1. **The count of bikes for season 3 with holiday is the most followed by without.**
2. **The least count of bikes in on season 1 with holiday.**

Based on Temp and atemp

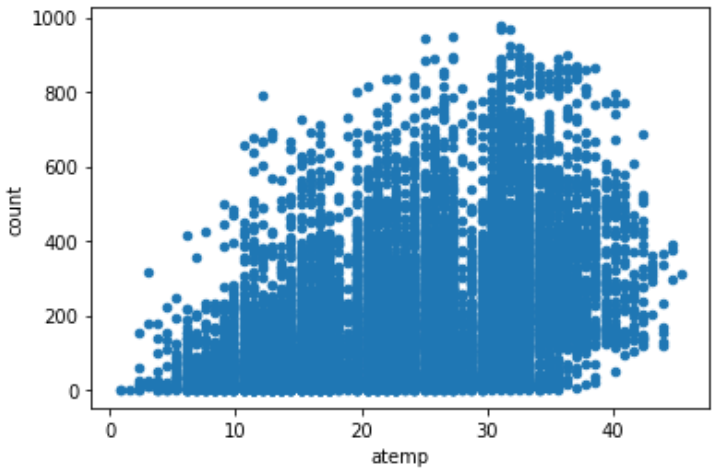
In [16]:

```
df.plot.scatter('temp', 'count')
plt.show()
```



In [17]:

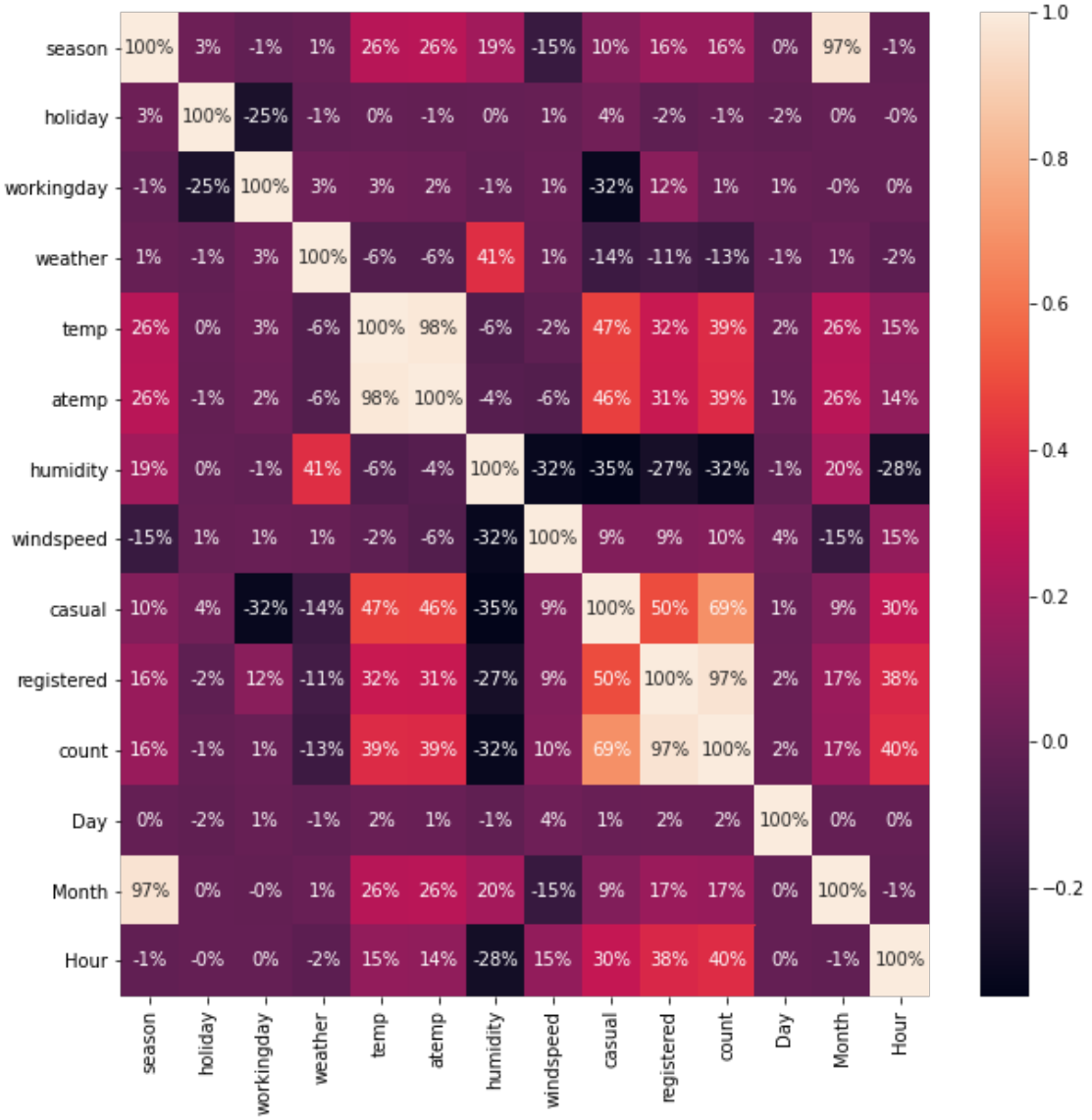
```
df.plot.scatter('atemp', 'count')
plt.show()
```



Correlation matrix

In [18]:

```
# Co-relation matrix
plt.figure(figsize = (10, 10))
sns.heatmap(df.corr(), annot = True, fmt = '.0%')
plt.show()
```



The correlation matrix provides the relation between two variables.

1. **We can see that, the humidity and count are in a correlation of -32% which means that as the humidity increases, the count decreases by 32%.**
2. **The weather and humidity has a correlation of 41%. This means as weather incrases, humidity increases by 41% and vice-versa.**

Conclusion

1. **The dataset predict the amount of bike rentals based on various parameters.**
2. **The rental bike count is analysed based on Month, day and hourly basis.**
3. **The dataset is analysed based on variables like weather, temperature, humidity.**
4. **The analysis using correlation is done.**