Bike Sharing in Washington DC

August 11, 2020

1 Bike Sharing in Washington DC Data Analysis

Link to the data: https://www.kaggle.com/marklvl/bike-sharing-dataset

Data Collection Date: 2011 and 2012

Data Source: 'Capital Bikeshare' https://www.capitalbikeshare.com/system-data

Possible Questions to explore:

1. How do variables like time of day, season, and weekday/weekend affect the number of bike rentals in a day?

[81]:
```
import numpy as np
import pandas as pd
import statsmodels.api as sm
```

[82]:
```
df = pd.read_csv('hour.csv')
df = df.rename(columns={'cnt': 'count'})
df['workingday'] = df['workingday'].replace({0: False, 1: True})
```

[83]:
```
df.head()
```

[83]:
```
   instant      dteday  season  yr  mnth  hr  holiday  weekday  workingday  \
0        1  2011-01-01       1   0     1   0        0        6       False
1        2  2011-01-01       1   0     1   1        0        6       False
2        3  2011-01-01       1   0     1   2        0        6       False
3        4  2011-01-01       1   0     1   3        0        6       False
4        5  2011-01-01       1   0     1   4        0        6       False

   weathersit  temp   atemp   hum  windspeed  casual  registered  count
0           1  0.24  0.2879  0.81        0.0       3          13     16
1           1  0.22  0.2727  0.80        0.0       8          32     40
2           1  0.22  0.2727  0.80        0.0       5          27     32
3           1  0.24  0.2879  0.75        0.0       3          10     13
4           1  0.24  0.2879  0.75        0.0       0           1      1
```

Description of the data can be found here: https://www.kaggle.com/marklvl/bike-sharing-dataset

[84]:
```
df.describe()
```

[84]:

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

            holiday       weekday    weathersit          temp         atemp  \
count  17379.000000  17379.000000  17379.000000  17379.000000  17379.000000
mean       0.028770      3.003683      1.425283      0.496987      0.475775
std        0.167165      2.005771      0.639357      0.192556      0.171850
min        0.000000      0.000000      1.000000      0.020000      0.000000
25%        0.000000      1.000000      1.000000      0.340000      0.333300
50%        0.000000      3.000000      1.000000      0.500000      0.484800
75%        0.000000      5.000000      2.000000      0.660000      0.621200
max        1.000000      6.000000      4.000000      1.000000      1.000000

                hum     windspeed        casual    registered         count
count  17379.000000  17379.000000  17379.000000  17379.000000  17379.000000
mean       0.627229      0.190098     35.676218    153.786869    189.463088
std        0.192930      0.122340     49.305030    151.357286    181.387599
min        0.000000      0.000000      0.000000      0.000000      1.000000
25%        0.480000      0.104500      4.000000     34.000000     40.000000
50%        0.630000      0.194000     17.000000    115.000000    142.000000
75%        0.780000      0.253700     48.000000    220.000000    281.000000
max        1.000000      0.850700    367.000000    886.000000    977.000000
```

1.1 How many total rentals were there?

[85]:

```
df['count'].sum()
```

[85]: 3292679

1.2 When were the peak hours for rentals?

[86]:

```
hourlyCount = df[['hr', 'count']].groupby('hr').sum()
```

[87]:

```
hourlyCount.head()
```

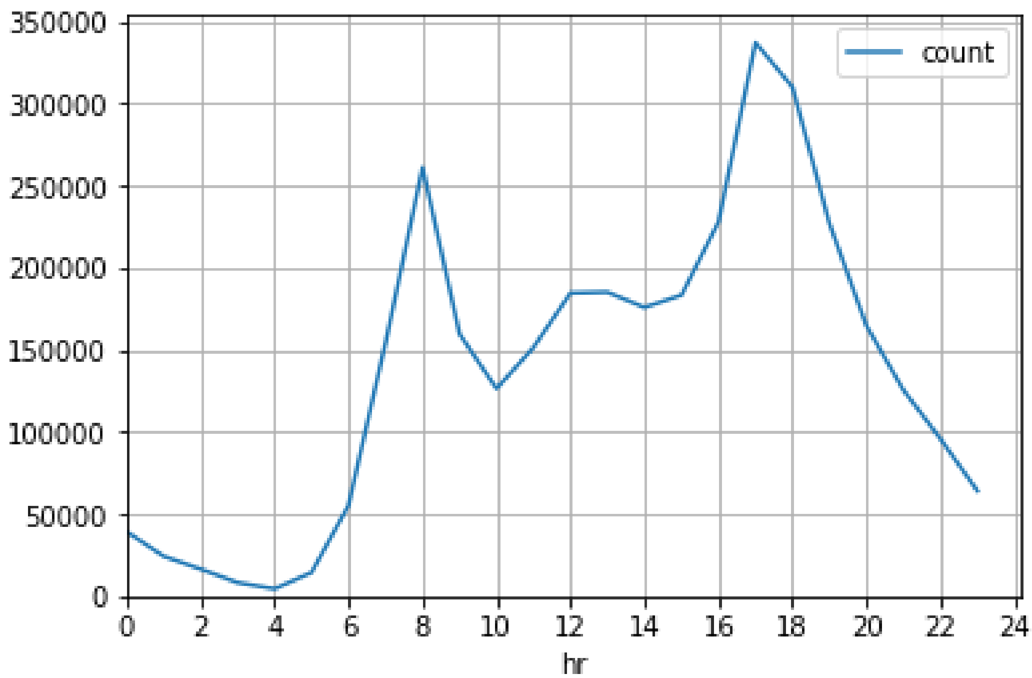
[87]:

```
    count
hr
```

```
0    39130
1    24164
2    16352
3     8174
4     4428
```

[88]:
```
hourlyCount.plot(xticks=range(0, 25, 2), grid=True, xlim=0, ylim=0)
```

[88]: <matplotlib.axes._subplots.AxesSubplot at 0x7fd7573ad490>



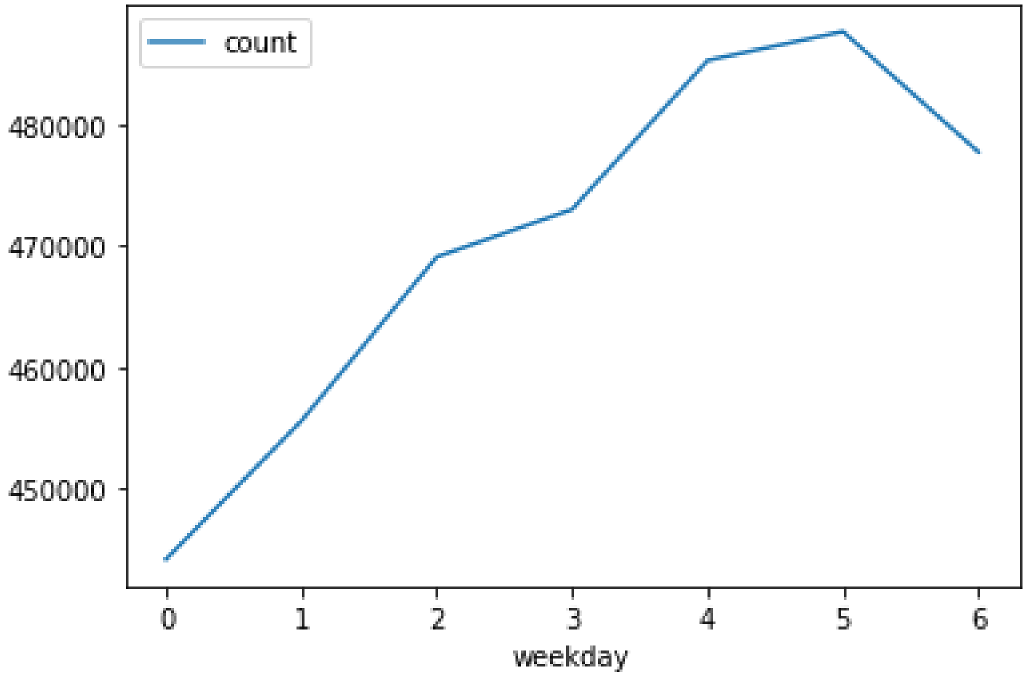
The peak hours for rentals was at 8 am and 5 pm. This makes sense as 8 am and 5 pm is usually the time for rush hour. These findings suggest that the most common usage of bike rentals is for commuting to work.

1.3 Are there more bike rentals on a weekday vs weekend?

[89]:
```
# 0 means Sunday, 1 means Monday, etc.

df[['weekday', 'count']].groupby('weekday').sum().plot(kind='line', rot=1)
```

[89]: <matplotlib.axes._subplots.AxesSubplot at 0x7fd7580a8e90>



We can use a hypothesis test to check if there is a significant difference. Technically since the data is taken from 2011 and 2012, it is not a simple random sample of all bike rides for this company.

Null hypothesis: There is no difference in bike rides per day on a weekday vs weekend. (proportion of rides = 0.5)

Alt hypothesis: There are more bike rides per day on a weekday. (proportion of rides > 0.5)

[90]:
```
Create a weekdaybool column and add it to the data set
```

```
  File "<ipython-input-90-4060e1ed4d45>", line 1
    Create a weekdaybool column and add it to the data set
           ^
SyntaxError: invalid syntax
```

[92]:
```
counts = df[['weekday', 'count']].groupby('weekday').sum()
counts = counts.reset_index()
```

[93]:
```
counts[(counts['weekday'] == 0) | (counts['weekday'] == 6)]
```

[93]:

	weekday	count
0	0	444027
6	6	477807

[94]:
```
# output of this function is (z-stat, p-value)
sm.stats.proportions_ztest(2292410, 2292410 + 1000269, 0.5,␣
↪alternative='two-sided')
```

[94]:
```
(774.1944548167168, 0.0)
```

The p-value is 0.0, so there is sufficient evidence to reject the null hypothesis that the proportion of bike rentals on a working day is 0.5. This finding shows that there are more bike rentals on a working day, which aligns with the previous finding that there are more bike rentals around rush hour.

[ ]:
```
# single regression of temp vs num of rides
# mult regression predicting # of rides or something
```

1.4 What is the relationship between temperature and number of rides on a day?

[24]:
```
df[['dteday', 'temp', 'count']].head()
```

[24]:

	dteday	temp	count
0	2011-01-01	0.24	16
1	2011-01-01	0.22	40
2	2011-01-01	0.22	32
3	2011-01-01	0.24	13
4	2011-01-01	0.24	1

According to the data source: "temp: Normalized temperature in Celsius. The values are derived via (t - tmin)/(tmax - tmin), tmin=-8, tmax=+39 (only in hourly scale)"

The data will be converted to farenheight for easier interpretation.

[26]:
```
tmin = -8
tmax = 39
```

[30]:
```
# temp in celsius, not normalized
celsius = (df['temp'] * (tmax - tmin)) + tmin
```

[31]:
```
# temp in fahrenheight, not normalized
fahrenheit = (celsius * 1.8) + 32
fahrenheit
```

[31]:
```
0        37.904
1        36.212
2        36.212
3        37.904
4        37.904
          …
```

```
17374    39.596
17375    39.596
17376    39.596
17377    39.596
17378    39.596
Name: temp, Length: 17379, dtype: float64
```

[32]:
```
df['temp'] = fahrenheit
```

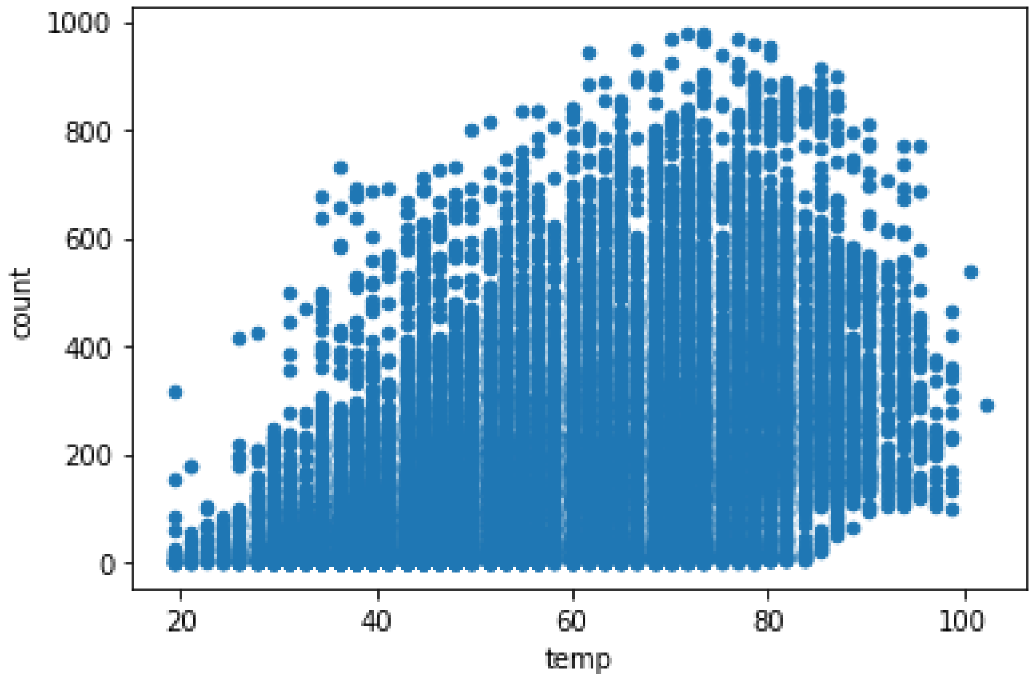
[40]:
```
df[['dteday', 'hr', 'temp', 'count']].head(13)
```

[40]:

	dteday	hr	temp	count
0	2011-01-01	0	37.904	16
1	2011-01-01	1	36.212	40
2	2011-01-01	2	36.212	32
3	2011-01-01	3	37.904	13
4	2011-01-01	4	37.904	1
5	2011-01-01	5	37.904	1
6	2011-01-01	6	36.212	2
7	2011-01-01	7	34.520	3
8	2011-01-01	8	37.904	8
9	2011-01-01	9	44.672	14
10	2011-01-01	10	49.748	36
11	2011-01-01	11	48.056	56
12	2011-01-01	12	53.132	84

[42]:
```
df[['temp', 'count']].plot(kind='scatter', x='temp', y='count')
```

[42]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd7519f1f50>
```



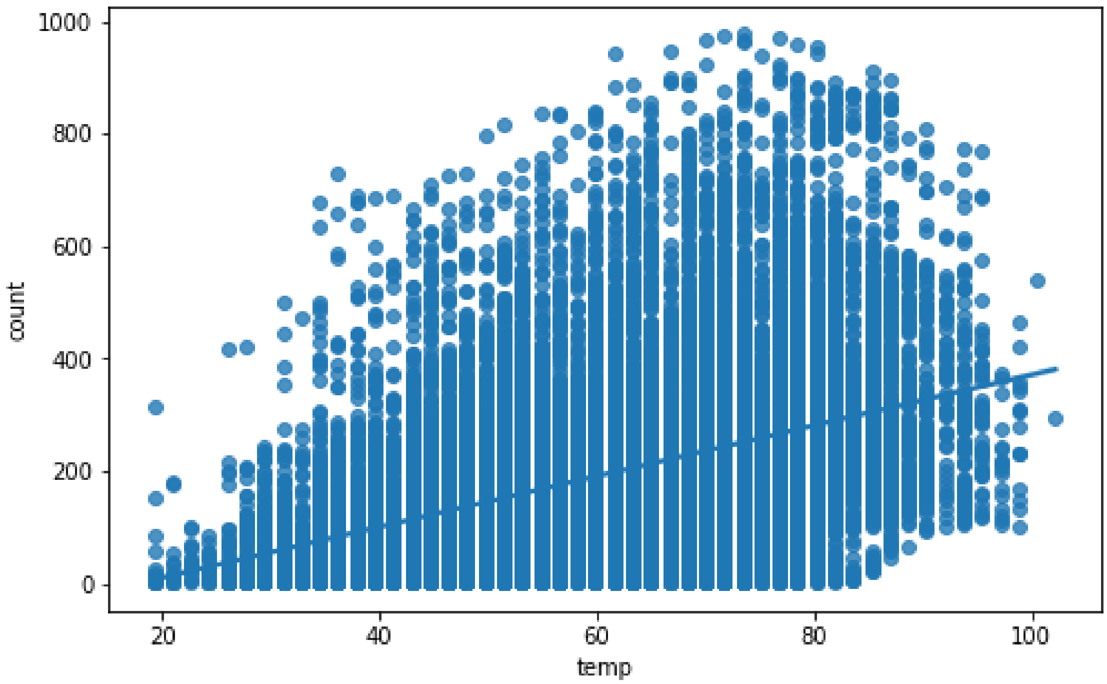
We will try to fit the data using linear regression and possibly polynomial regression if a linear model is not a good fit.

[44]:
```
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

[48]:
```
from sklearn.linear_model import LinearRegression
```

[54]:
```
plt.figure(figsize=(8, 5))
sns.regplot(x='temp', y='count', data=df)
```

[54]: <matplotlib.axes._subplots.AxesSubplot at 0x7fd754458c10>

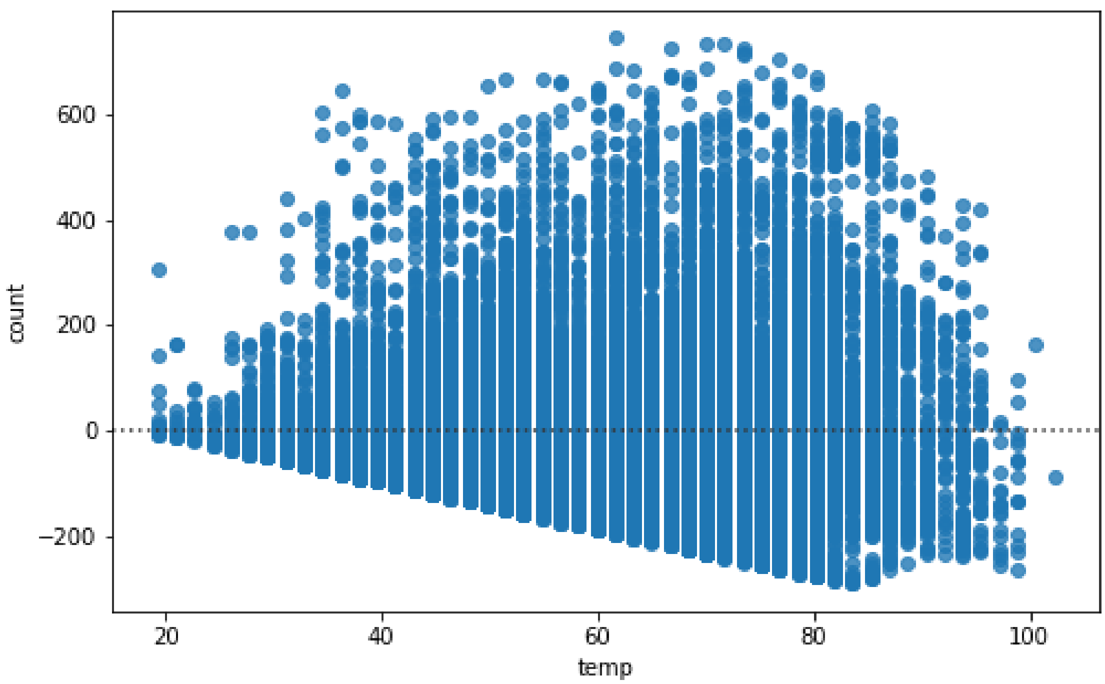


[55]:
```
lm = LinearRegression()
X = df[['temp']]
Y = df['count']
lm.fit(X,Y)
lm.score(X,Y) #R-squared value
```

[55]: 0.16384059523903416

[57]:
```
plt.figure(figsize=(8, 5))
sns.residplot(df['temp'], df['count'])
```

[57]: <matplotlib.axes._subplots.AxesSubplot at 0x7fd7544a2e10>

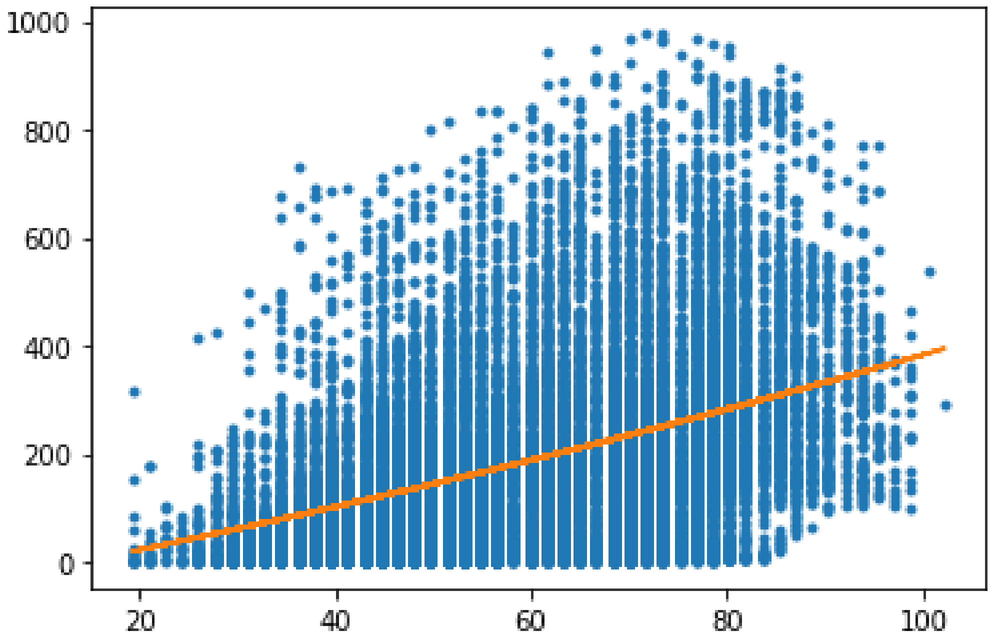


The linear model has an R-squared value of 0.16 and the residual plot does not show a random scatter making this linear model a poor fit for the data. A 2nd order polynomial regression may be more reasonable because people won't want to ride a bike if the weather is too cold or too hot.

[65]:
```
coeff = np.polyfit(df['temp'], df['count'], 2)
pm = np.poly1d(poly)
```

[69]:
```
plt.plot(df['temp'], df['count'], '.', df['temp'], pm(df['temp']), '-')
```

[69]:
```
[<matplotlib.lines.Line2D at 0x7fd75515bdd0>,
 <matplotlib.lines.Line2D at 0x7fd75506fe50>]
```



[ ]:
```
# split up for each season
```

[ ]:

[ ]:

[ ]: