Cycle Data Prediction by weather 10-DBConnect

March 23, 2018

1 Cycle Data Prediction by Weather

Declaration : The central idea and coding is abstract from Kevin mark ham youtube video seriese, Introduction to machine learning with scikit-learn video series. You can find link under resources section.

Question How many bike rentals would we predict if the temperature given in degrees Celsius?

Question Does the scale of the features matter?

Question what are effect cause by weather on bike rental scheme?

2 Libraries

```
In [16]: import os,csv,io,mapsplotlib,time,folium,googlemaps,geopy,zipfile,requests,warnings
         import numpy as np
         import pandas as pd
         import datetime as dt
         import seaborn as sns
         import geopandas as gpd
         from shapely.geometry import Point
         import statsmodels.formula.api as smf
         import matplotlib.pyplot as plt
         import mysql.connector as sql
         from sklearn.linear_model import LinearRegression
         model = LinearRegression()
         from sklearn import metrics
         from sklearn.cross_validation import train_test_split
         from sklearn.svm import LinearSVC
         import numpy as np
         warnings.simplefilter('ignore')

         # display plots in the notebook
         %matplotlib inline

         # increase default figure and font sizes for easier viewing
         plt.rcParams['figure.figsize'] = (8, 6)
         plt.rcParams['font.size'] = 14
```

In [17]:
```python
#importing data from database
db_connection = sql.connect(host='localhost', database='bike', user='root', password=
db_cursor = db_connection.cursor()
db_cursor.execute('SELECT twdate Date,Bike_rented total,Mean_Temperature_C temp,Max_Te
table_rows = db_cursor.fetchall()
data = pd.read_sql('SELECT twdate Date,Bike_rented total,Mean_Temperature_C temp,Max_T
bikes = pd.DataFrame(data)
bikes.dtypes
```

Out[17]:
```
Date                 object
total                 int64
temp                  int64
Maxf                  int64
Minf                  int64
Maxhum                int64
Minhum                int64
Visibility_Miles      int64
Wind_Speed_MPH        int64
Precipitation_In    float64
Events_num            int64
Events               object
month                 int64
year                  int64
dtype: object
```

In [35]:
```python
bikes.tail()
```

Out[35]:
```
           Date  total  temp  Maxf  Minf  Maxhum  Minhum  Visibility_Miles  \
604  2016-08-27     60    18    72    61      81      46                10
605  2016-08-28     76    20    75    59      80      44                10
606  2016-08-29    200    20    81    55      89      39                10
607  2016-08-30    208    17    70    57      83      53                10
608  2016-08-31    178    18    71    59      90      63                10

     Wind_Speed_MPH  Precipitation_In  Events_num Events  month  year
604               9               0.0           6  Sunny      8  2016
605               9               0.0           6  Sunny      8  2016
606               4               0.0           6  Sunny      8  2016
607               9               0.0           6  Sunny      8  2016
608               8               0.0           6  Sunny      8  2016
```

In [19]:
```python
bikes.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 609 entries, 0 to 608
Data columns (total 14 columns):
Date                   609 non-null object
total                  609 non-null int64
temp                   609 non-null int64
```

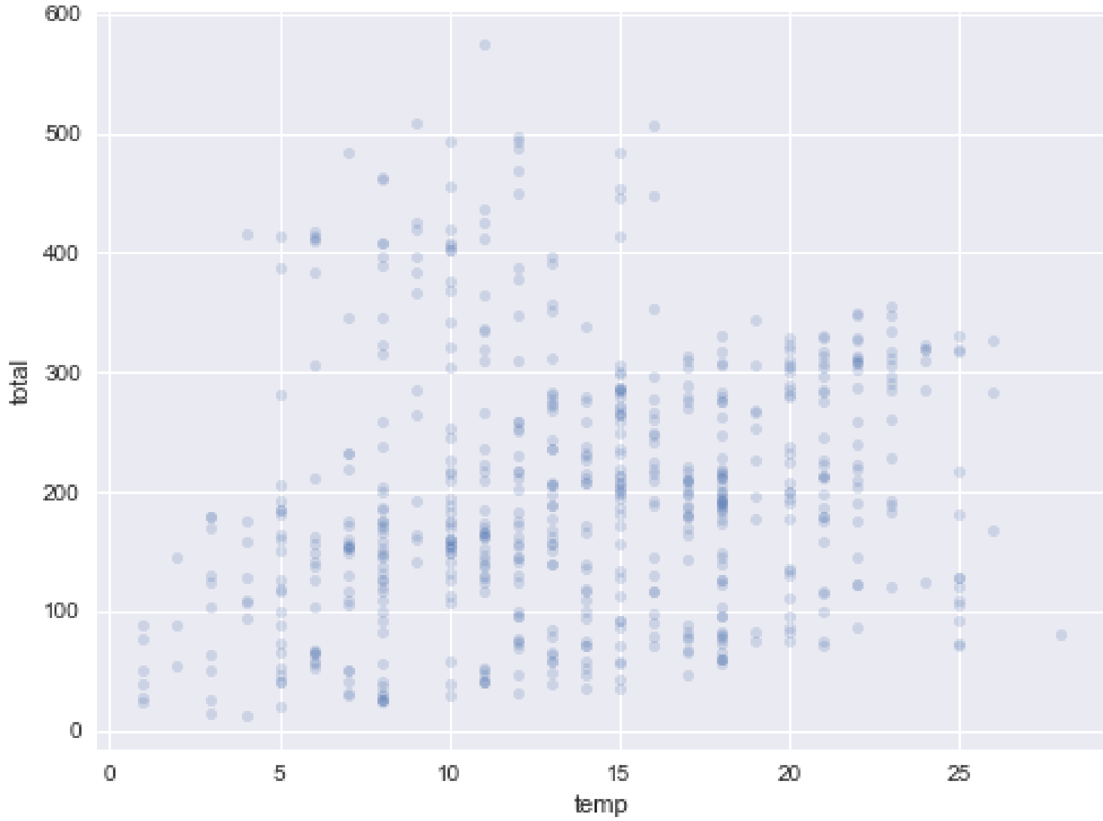
```
Maxf                 609 non-null int64
Minf                 609 non-null int64
Maxhum               609 non-null int64
Minhum               609 non-null int64
Visibility_Miles     609 non-null int64
Wind_Speed_MPH       609 non-null int64
Precipitation_In     609 non-null float64
Events_num           609 non-null int64
Events               609 non-null object
month                609 non-null int64
year                 609 non-null int64
dtypes: float64(1), int64(11), object(2)
memory usage: 66.7+ KB
```

2.1 Visualizing the data

```
In [20]: import seaborn as sns
         import matplotlib.pyplot as plt
         %matplotlib inline
         plt.rcParams['figure.figsize'] = (8, 6)
         plt.rcParams['font.size'] = 14
```

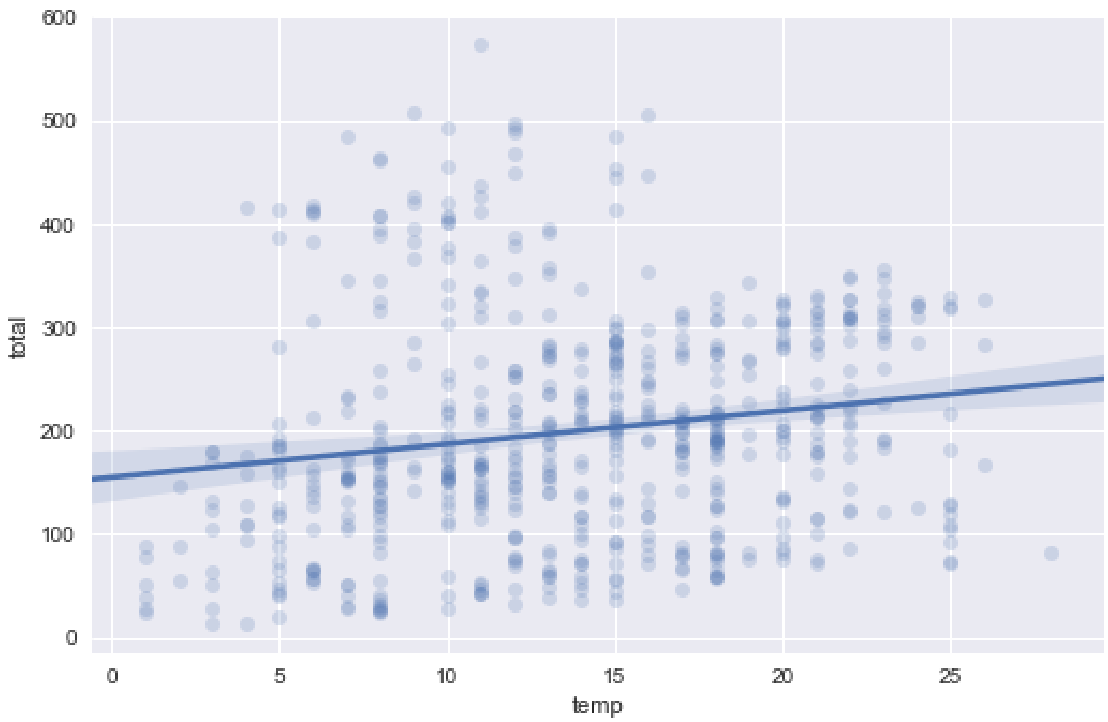
```
In [21]: # Pandas scatter plot
         bikes.plot(kind='scatter', x='temp', y='total', alpha=0.2)
```

```
Out[21]: <matplotlib.axes._subplots.AxesSubplot at 0x1bb2c085978>
```




```
In [22]: # Seaborn scatter plot with regression line
         sns.lmplot(x='temp', y='total', data=bikes, aspect=1.5, scatter_kws={'alpha':0.2})

Out[22]: <seaborn.axisgrid.FacetGrid at 0x1bb2c4dbfd0>
```



3 Building a linear regression model

```
In [64]: # create X and y where temp is the temprature and total is a total observation
         feature_cols = ['temp']
         X = bikes[feature_cols]
         y = bikes.total

In [65]: # import, instantiate, fit
         from sklearn.linear_model import LinearRegression
         linreg = LinearRegression()
         linreg.fit(X, y)

Out[65]: LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normalize=False)

In [66]: # print the coefficients
         print (linreg.intercept_)
         print (linreg.coef_)

154.859661305
[ 3.22495402]
```

3.1 Using the model for prediction

```
In [67]: # use the predict method
         a = linreg.predict(20)
         print (a)
```

```
[ 219.35874174]
```

3.2 Conclusion:

The Model predicted that when temperature reach to 20 degrees Celsius there is a chance of ***121*** bicycle could be rented.

3.3 Does the scale of the features matter?

Let's say that temperature was measured in Fahrenheit, rather than Celsius. How would that affect the model?

```
In [68]: # create a new column for Fahrenheit temperature
         bikes['temp_F'] = bikes.temp * 1.8 + 32
         bikes.head()
```

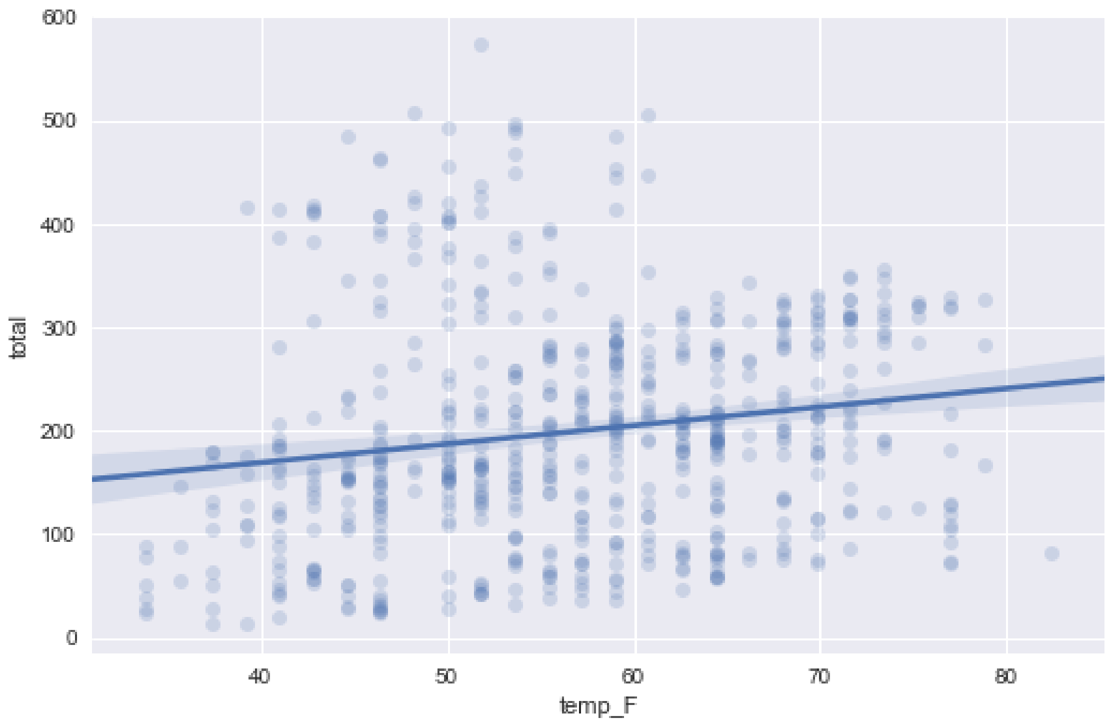
Out[68]:

	Date	total	temp	Maxf	Minf	Maxhum	Minhum	Visibility_Miles	\
0	2015-01-01	88	1	43	27	81	49	10	
1	2015-01-02	180	3	44	32	86	67	10	
2	2015-01-03	104	3	43	33	93	76	7	
3	2015-01-04	56	8	54	41	89	77	8	
4	2015-01-05	244	13	57	54	88	74	8	

	Wind_Speed_MPH	Precipitation_In	Events_num	Events	month	year	temp_F
0	0	0.00	2	Rain	1	2015	33.8
1	4	0.03	2	Rain	1	2015	37.4
2	2	0.00	2	Rain	1	2015	37.4
3	7	0.22	2	Rain	1	2015	46.4
4	14	0.07	2	Rain	1	2015	55.4

```
In [69]: # Seaborn scatter plot with regression line
         sns.lmplot(x='temp_F', y='total', data=bikes, aspect=1.5, scatter_kws={'alpha':0.2})
```

```
Out[69]: <seaborn.axisgrid.FacetGrid at 0x1bb2d90eeb8>
```




```
In [70]: # create X and y
         feature_cols = ['temp_F']
         X = bikes[feature_cols]
         y = bikes.total

         # instantiate and fit
         linreg = LinearRegression()
         linreg.fit(X, y)

         # print the coefficients
         print (linreg.intercept_)
         print (linreg.coef_)
```

```
97.5271453636
[ 1.79164112]
```

```
In [71]: # convert 20 degrees Celsius to Fahrenheit
         20 * 1.8 + 32
```

```
Out[71]: 68.0
```

```
In [72]: # predict rentals for 68 degrees Fahrenheit
         b = linreg.predict(68)
         print (b)
```

```
[ 219.35874174]
```

4 The difference

```
In [73]: print ('Total difference in prediction form Celsius to Fahrenheit:',(b-a))
```

```
Total difference in prediction form Celsius to Fahrenheit: [ 0.]
```

The result shows that the scale of the features does not matter.As, both scales predict the same values of result

Conclusion: The scale of the features is **irrelevant** for linear regression models. When changing the scale, we simply change our **interpretation** of the coefficients.

5 Visualizing the data (part 2)

```
In [78]: # explore more features
         feature_cols = ['temp', 'Events_num', 'Visibility_Miles', 'Wind_Speed_MPH']
```

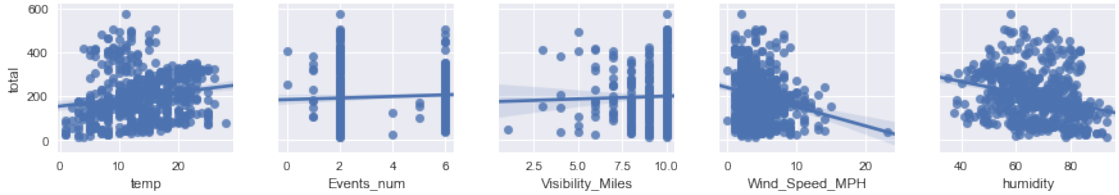
```
In [83]: #importing data from database
         db_connection = sql.connect(host='localhost', database='bike', user='root', password=
         db_cursor = db_connection.cursor()
         db_cursor.execute('SELECT Events_num,Events FROM trip_weather group by  Events_num')
         table_rows = db_cursor.fetchall()
         data = pd.read_sql('SELECT Events_num,Events FROM trip_weather group by  Events_num',
         bikes = pd.DataFrame(data)
         bikes
```

Out[83]:

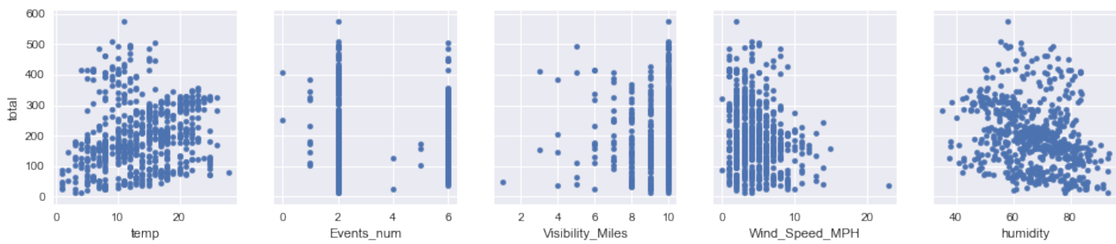
	Events_num	Events
0	0	Fog
1	1	Fog, Rain
2	2	Rain
3	4	Rain-Snow
4	5	Rain-Thunderstorm
5	6	Sunny

```
In [197]: #importing data from database
          db_connection = sql.connect(host='localhost', database='bike', user='root', password=
          db_cursor = db_connection.cursor()
          db_cursor.execute('SELECT twdate Date,Bike_rented total,Mean_Temperature_C temp,Max_
          table_rows = db_cursor.fetchall()
          data = pd.read_sql('SELECT twdate Date,Bike_rented total,Mean_Temperature_C temp,Max_
          bikes = pd.DataFrame(data)
          bikes['humidity']=(bikes.Maxhum + bikes.Minhum)/2
          # explore more features
          feature_cols = ['temp', 'Events_num', 'Visibility_Miles', 'Wind_Speed_MPH', 'humidity
          # multiple scatter plots in Seaborn
          sns.pairplot(bikes, x_vars=feature_cols, y_vars='total', kind='reg')
```

Out[197]: <seaborn.axisgrid.PairGrid at 0x1bb2e57e390>



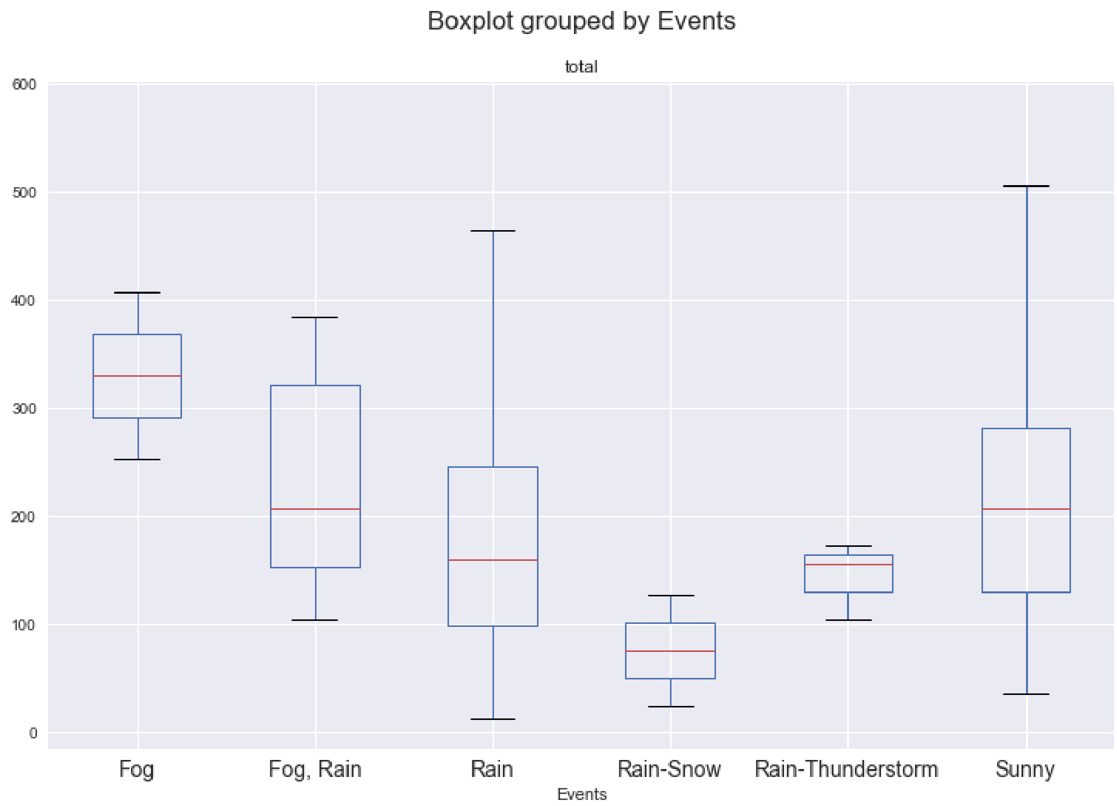
In [198]:
```
# multiple scatter plots in Pandas
fig, axs = plt.subplots(1, len(feature_cols), sharey=True)
for index, feature in enumerate(feature_cols):
    bikes.plot(kind='scatter', x=feature, y='total', ax=axs[index], figsize=(16, 3))
```



6 Bicycle rentals by Events

In [199]:
```
# increase default figure and font sizes for easier viewing
plt.rcParams['figure.figsize'] = (12, 8)
plt.rcParams['font.size'] = 14
# box plot of rentals, grouped by season
bikes.boxplot(column='total', by='Events')
```

Out[199]: <matplotlib.axes._subplots.AxesSubplot at 0x1bb2e76fe10>

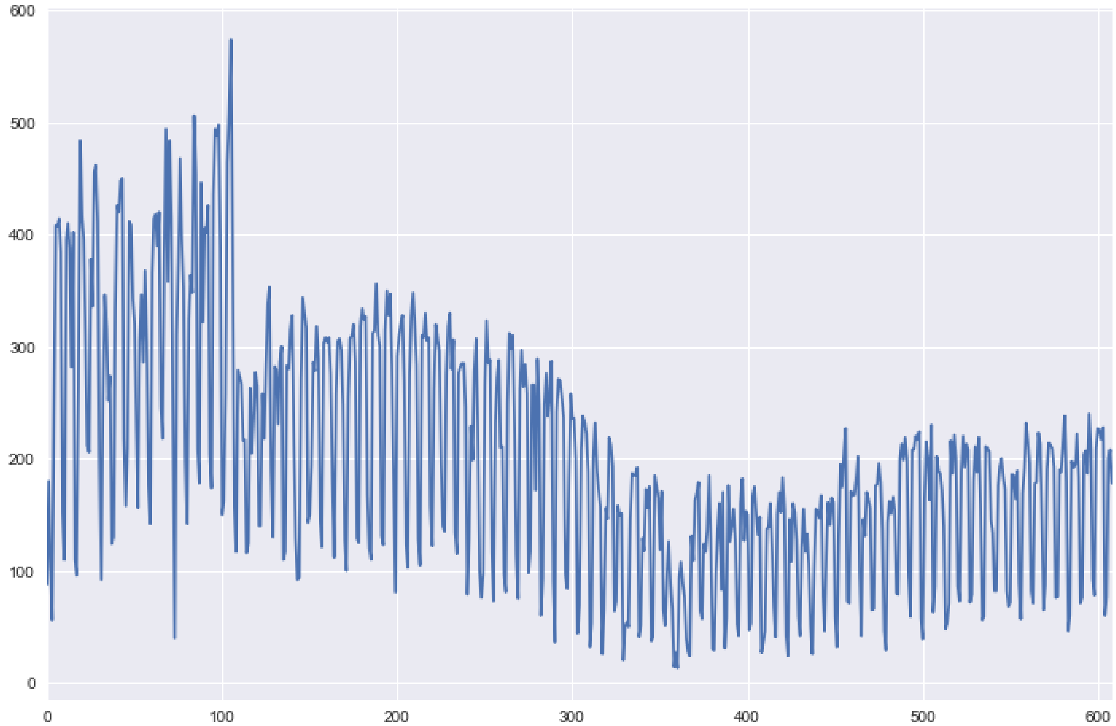


Notably:

- A line can't capture a non-linear relationship.
- There are less rentals in winter than in spring (?)

In [200]:
```
# line plot of rentals
bikes.total.plot()
```

Out[200]: `<matplotlib.axes._subplots.AxesSubplot at 0x1bb2e7c3518>`



What does this tell us?

There are less rentals in the winter than the spring, but only because the system is experiencing **overall decay** and the winter months happen to come after the spring months.

In [201]:
```
# correlation matrix (ranges from 1 to -1)
bikes.corr()
```

Out[201]:

	total	temp	Maxf	Minf	Maxhum	Minhum	\
total	1.000000	0.171038	0.191137	0.128383	-0.288507	-0.221978	
temp	0.171038	1.000000	0.969747	0.946960	-0.629958	-0.606063	
Maxf	0.191137	0.969747	1.000000	0.850083	-0.628851	-0.715949	
Minf	0.128383	0.946960	0.850083	1.000000	-0.573038	-0.403204	
Maxhum	-0.288507	-0.629958	-0.628851	-0.573038	1.000000	0.647923	
Minhum	-0.221978	-0.606063	-0.715949	-0.403204	0.647923	1.000000	
Visibility_Miles	0.028374	0.361507	0.385667	0.285961	-0.335181	-0.481033	
Wind_Speed_MPH	-0.223263	-0.059260	-0.142499	0.049577	0.152543	0.276615	
Precipitation_In	-0.241635	-0.239945	-0.296065	-0.148468	0.321042	0.422462	
Events_num	0.066881	0.825399	0.806354	0.788437	-0.510689	-0.493925	
month	-0.153841	0.282011	0.250732	0.303514	-0.239915	-0.177272	
year	-0.444737	-0.009845	0.013180	-0.040700	0.372230	0.064655	
humidity	-0.271274	-0.674047	-0.747567	-0.513429	0.858473	0.946872	

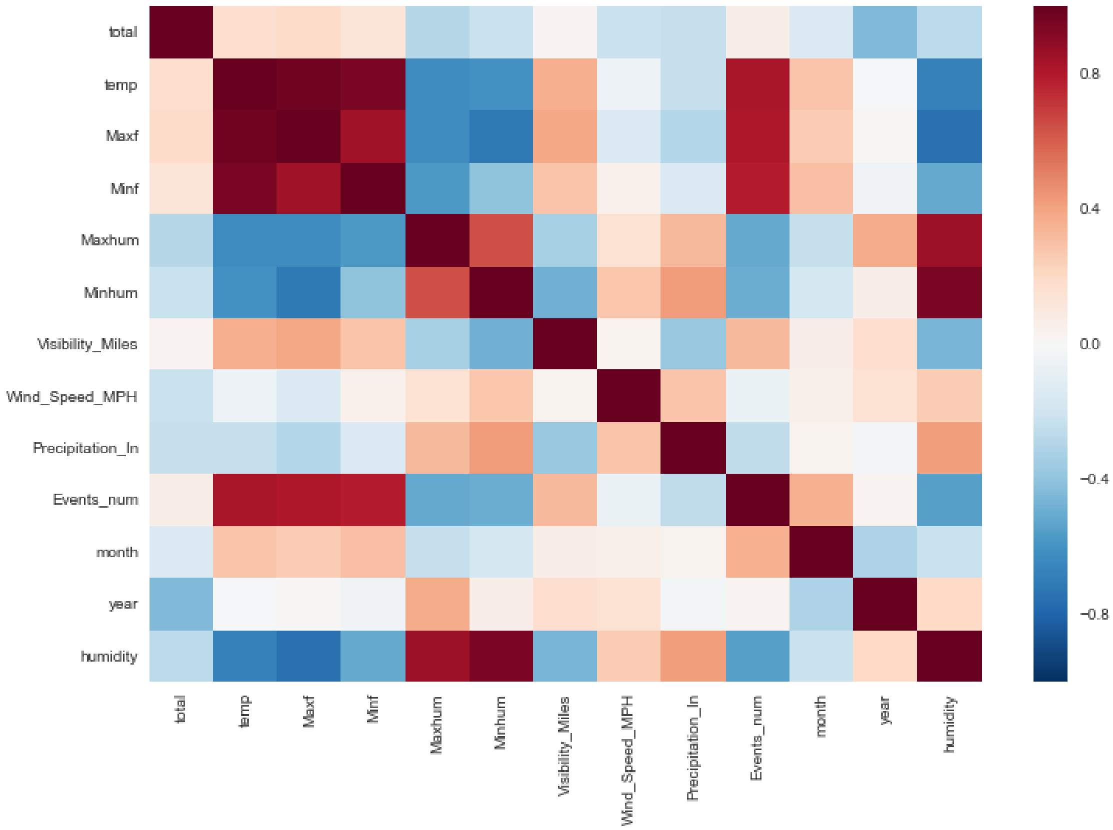
	Visibility_Miles	Wind_Speed_MPH	Precipitation_In	\
total	0.028374	-0.223263	-0.241635	
temp	0.361507	-0.059260	-0.239945	

```
Maxf                     0.385667       -0.142499         -0.296065
Minf                     0.285961        0.049577         -0.148468
Maxhum                  -0.335181        0.152543          0.321042
Minhum                  -0.481033        0.276615          0.422462
Visibility_Miles         1.000000        0.034379         -0.382224
Wind_Speed_MPH           0.034379        1.000000          0.287960
Precipitation_In        -0.382224        0.287960          1.000000
Events_num               0.327864       -0.066293         -0.256100
month                    0.066043        0.058717          0.033554
year                     0.171817        0.149078         -0.030281
humidity                -0.465402        0.250653          0.419997

                  Events_num     month      year  humidity
total               0.066881 -0.153841 -0.444737 -0.271274
temp                0.825399  0.282011 -0.009845 -0.674047
Maxf                0.806354  0.250732  0.013180 -0.747567
Minf                0.788437  0.303514 -0.040700 -0.513429
Maxhum             -0.510689 -0.239915  0.372230  0.858473
Minhum             -0.493925 -0.177272  0.064655  0.946872
Visibility_Miles    0.327864  0.066043  0.171817 -0.465402
Wind_Speed_MPH     -0.066293  0.058717  0.149078  0.250653
Precipitation_In   -0.256100  0.033554 -0.030281  0.419997
Events_num          1.000000  0.354204  0.024837 -0.548186
month               0.354204  1.000000 -0.308230 -0.220656
year                0.024837 -0.308230  1.000000  0.200697
humidity           -0.548186 -0.220656  0.200697  1.000000
```

In [203]:
```
# visualize correlation matrix in Seaborn using a heatmap
sns.heatmap(bikes.corr())
```

Out[203]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1bb312e8b70>
```



7 Relationships between variables

```
In [204]: #importing data from database
          db_connection = sql.connect(host='localhost', database='bike', user='root', password=
          db_cursor = db_connection.cursor()
          db_cursor.execute('SELECT twdate Date,Bike_rented total,Mean_Temperature_C temp,Max_
          table_rows = db_cursor.fetchall()
          data = pd.read_sql('SELECT twdate Date,Bike_rented total,Mean_Temperature_C temp,Max_
          bikes = pd.DataFrame(data)
```

```
In [205]: bikes['humidity']=(bikes.Maxhum + bikes.Minhum)/2
          bikes.head()
```

Out[205]:

	Date	total	temp	Maxf	Minf	Maxhum	Minhum	Visibility_Miles	\
0	2015-01-01	88	1	43	27	81	49	10	
1	2015-01-02	180	3	44	32	86	67	10	
2	2015-01-03	104	3	43	33	93	76	7	
3	2015-01-04	56	8	54	41	89	77	8	
4	2015-01-05	244	13	57	54	88	74	8	

```
   Wind_Speed_MPH  Precipitation_In  Events_num Events  month  year  humidity
0               0              0.00           2   Rain      1  2015      65.0
1               4              0.03           2   Rain      1  2015      76.5
2               2              0.00           2   Rain      1  2015      84.5
3               7              0.22           2   Rain      1  2015      83.0
4              14              0.07           2   Rain      1  2015      81.0
```

```
In [206]: # create a list of features
          feature_cols = ['temp','Wind_Speed_MPH','humidity','Precipitation_In','Events_num']
```

```
In [207]: # create X and y
          X = bikes[feature_cols]
          y = bikes.total

          # instantiate and fit
          linreg = LinearRegression()
          linreg.fit(X, y)

          # print the coefficients
          print (linreg.intercept_)
          print (linreg.coef_)
```

```
324.615572274
[  4.50336385  -5.72943396  -1.46296321 -68.53515488 -14.09003739]
```

```
In [208]: # pair the feature names with the coefficients
          zip(feature_cols, linreg.coef_)
```

```
Out[208]: <zip at 0x1bb3139a6c8>
```

```
In [209]: BabyDataSet = zip(feature_cols,linreg.coef_)
```

```
In [210]: #importing data from database
          db_connection = sql.connect(host='localhost', database='bike', user='root', password=
          db_cursor = db_connection.cursor()
          db_cursor.execute('SELECT Events_num,Events FROM trip_weather group by  Events_num')
          table_rows = db_cursor.fetchall()
          data = pd.read_sql('SELECT Events_num,Events FROM trip_weather group by  Events_num'
          bikes = pd.DataFrame(data)
          bikes
```

```
Out[210]:    Events_num              Events
          0           0                 Fog
          1           1           Fog, Rain
          2           2                Rain
          3           4           Rain-Snow
          4           5  Rain-Thunderstorm
          5           6               Sunny
```

In [211]:
```
BabyDataSet = list(zip(feature_cols,linreg.coef_))
BabyDataSet
```

Out[211]:
```
[('temp', 4.5033638461235732),
 ('Wind_Speed_MPH', -5.7294339568329979),
 ('humidity', -1.4629632078092731),
 ('Precipitation_In', -68.535154877134516),
 ('Events_num', -14.090037389117011)]
```

Interpreting the coefficients:

- Holding all other features fixed, a 1 unit increase in **temperature** is associated with a **rental increase of 4.50 bikes**.
- Holding all other features fixed, a 1 unit increase in **'Wind_Speed_MPH** is associated with a **rental decrease of -5.72 bikes**.
- Holding all other features fixed, a 1 unit increase in **humidity** is associated with a **rental decrease of -1.46 bikes**.
- Holding all other features fixed, a 1 unit increase in **Precipitation_In** is associated with a **rental decrease of -68.53 bikes**.
- Holding all other features fixed, a 1 unit increase in **Events_num** is associated with a **rental decrease of -14.09 bikes**

In [212]:
```
# example true and predicted response values
true = [10, 7, 5, 5]
pred = [8, 6, 5, 10]
```

In [213]:
```
# calculate these metrics by hand!
from sklearn import metrics
import numpy as np
print ('MAE:', metrics.mean_absolute_error(true, pred))
print ('MSE:', metrics.mean_squared_error(true, pred))
print ('RMSE:', np.sqrt(metrics.mean_squared_error(true, pred)))
```

```
MAE: 2.0
MSE: 7.5
RMSE: 2.73861278753
```

In [214]:
```
# same true values as above
true = [10, 7, 5, 5]

# new set of predicted values
pred = [10, 7, 5, 13]

# MAE is the same as before
print ('MAE:', metrics.mean_absolute_error(true, pred))
```

```
# MSE and RMSE are larger than before
print ('MSE:', metrics.mean_squared_error(true, pred))
print ('RMSE:', np.sqrt(metrics.mean_squared_error(true, pred)))
```

```
MAE: 2.0
MSE: 16.0
RMSE: 4.0
```

As we can notice that after applying some new set of predicted values. The model shows very different result. The value of MAE is the same before, but mean squared error and root mean squared error are larger than before.

8 Comparing models with train/test split and RMSE

In [215]:
```
#importing data from database
db_connection = sql.connect(host='localhost', database='bike', user='root', password=
db_cursor = db_connection.cursor()
db_cursor.execute('SELECT twdate Date,Bike_rented total,Mean_Temperature_C temp,Max_
table_rows = db_cursor.fetchall()
data = pd.read_sql('SELECT twdate Date,Bike_rented total,Mean_Temperature_C temp,Max_
bikes = pd.DataFrame(data)
```

In [216]:
```
bikes['humidity']=(bikes.Maxhum + bikes.Minhum)/2
bikes.head()
```

Out[216]:
```
         Date  total  temp  Maxf  Minf  Maxhum  Minhum  Visibility_Miles  \
0  2015-01-01     88     1    43    27      81      49                10
1  2015-01-02    180     3    44    32      86      67                10
2  2015-01-03    104     3    43    33      93      76                 7
3  2015-01-04     56     8    54    41      89      77                 8
4  2015-01-05    244    13    57    54      88      74                 8

   Wind_Speed_MPH  Precipitation_In  Events_num Events  month  year  humidity
0               0              0.00           2   Rain      1  2015      65.0
1               4              0.03           2   Rain      1  2015      76.5
2               2              0.00           2   Rain      1  2015      84.5
3               7              0.22           2   Rain      1  2015      83.0
4              14              0.07           2   Rain      1  2015      81.0
```

9 Features selection

In [223]:
```
# create a list of features
feature_cols = ['temp','Wind_Speed_MPH','humidity','Precipitation_In','Events_num']
```

In [224]:
```
from sklearn.cross_validation import train_test_split
```

```
# define a function that accepts a list of features and returns testing RMSE
def train_test_rmse(feature_cols):
    X = bikes[feature_cols]
    y = bikes.total
    X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=123)
    linreg = LinearRegression()
    linreg.fit(X_train, y_train)
    y_pred = linreg.predict(X_test)
    return np.sqrt(metrics.mean_squared_error(y_test, y_pred))
```

```
In [218]: # compare different sets of features
          print (train_test_rmse(['temp','Wind_Speed_MPH','humidity','Precipitation_In','Events
          print (train_test_rmse(['temp','Wind_Speed_MPH','humidity','Precipitation_In']))
          print (train_test_rmse(['temp','Wind_Speed_MPH','humidity']))
```

```
95.6891372885
98.1231782742
98.3398920602
```

```
In [225]: print (train_test_rmse(['temp','Wind_Speed_MPH','humidity','Events_num']))
```

```
96.3085655303
```

```
In [226]: print (train_test_rmse(['temp','humidity','Events_num']))
```

```
98.3802263221
```

```
In [227]: print (train_test_rmse(['Wind_Speed_MPH','humidity','Events_num']))
```

```
97.8009125859
```

```
In [228]: print (train_test_rmse(['temp']))
```

```
99.8054559912
```

```
In [229]: print (train_test_rmse(['temp','Wind_Speed_MPH']))
```

```
97.309087016
```

```
In [230]: print (train_test_rmse(['temp','Wind_Speed_MPH','humidity','Precipitation_In','Events
```

```
95.6891372885
```

From the RMSE result, I decided to keep above columns.

9.1 Comparing testing RMSE with null RMSE

Null RMSE is the RMSE that could be achieved by **always predicting the mean response value**. It is a benchmark against which we may want to measure our regression model.

```
In [219]: # split X and y into training and testing sets
          X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=123)

          # create a NumPy array with the same shape as y_test
          y_null = np.zeros_like(y_test, dtype=float)

          # fill the array with the mean value of y_test
          y_null.fill(y_test.mean())
          y_null
```

```
Out[219]: array([ 190.69281046,  190.69281046,  190.69281046,  190.69281046,
                  190.69281046,  190.69281046,  190.69281046,  190.69281046,
                  190.69281046,  190.69281046,  190.69281046,  190.69281046,
                  190.69281046,  190.69281046,  190.69281046,  190.69281046,
                  190.69281046,  190.69281046,  190.69281046,  190.69281046,
                  190.69281046,  190.69281046,  190.69281046,  190.69281046,
                  190.69281046,  190.69281046,  190.69281046,  190.69281046,
                  190.69281046,  190.69281046,  190.69281046,  190.69281046,
                  190.69281046,  190.69281046,  190.69281046,  190.69281046,
                  190.69281046,  190.69281046,  190.69281046,  190.69281046,
                  190.69281046,  190.69281046,  190.69281046,  190.69281046,
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                  190.69281046,  190.69281046,  190.69281046,  190.69281046,
                  190.69281046,  190.69281046,  190.69281046,  190.69281046,
                  190.69281046,  190.69281046,  190.69281046,  190.69281046,
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                  190.69281046,  190.69281046,  190.69281046,  190.69281046,
                  190.69281046,  190.69281046,  190.69281046,  190.69281046,
                  190.69281046,  190.69281046,  190.69281046,  190.69281046,
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                  190.69281046,  190.69281046,  190.69281046,  190.69281046,
                  190.69281046,  190.69281046,  190.69281046,  190.69281046,
                  190.69281046,  190.69281046,  190.69281046,  190.69281046,
```

```
         190.69281046,  190.69281046,  190.69281046,  190.69281046,
         190.69281046,  190.69281046,  190.69281046,  190.69281046,
         190.69281046,  190.69281046,  190.69281046,  190.69281046,
         190.69281046,  190.69281046,  190.69281046,  190.69281046,
         190.69281046])
```

```
In [222]: # compute null RMSE
          print ('Predicting the mean response value:',np.sqrt(metrics.mean_squared_error(y_te
```

```
Predicting the mean response value: 102.007386702
```

9.2 Conclusion:

Question How many bike rentals would we predict if the temperature given in degrees Celsius?

- The Model predicted that when temperature reach to 20 degrees Celsius there is a chance of ***121*** bicycle could be rented.

Question Does the scale of the features matter?
-The scale of the features is **irrelevant** for linear regression models. When changing the scale, we simply change our **interpretation** of the coefficients.
Question what are effect cause by weather on bike rental scheme?

- Holding all other features fixed, a 1 unit increase in **temperature** is associated with a **rental increase of 4.50 bikes**.
- Holding all other features fixed, a 1 unit increase in **'Wind_Speed_MPH** is associated with a **rental decrease of -5.72 bikes**.
- Holding all other features fixed, a 1 unit increase in **humidity** is associated with a **rental decrease of -1.46 bikes**.
- Holding all other features fixed, a 1 unit increase in **Precipitation_In** is associated with a **rental decrease of -68.53 bikes**.
- Holding all other features fixed, a 1 unit increase in **Events_num** is associated with a **rental decrease of -14.09 bikes**
- From the obtain result, after applying some new set of predicted values. The model shows very different result. The value of MAE is the same before, but mean squared error and root mean squared error are larger than before. That's change in predicted values will effect on MSE and RMSE. The lower the RMSE is better. So, we could conclude that change in weather condition will effect on Bike Rental.

9.3 Resources

References:*From the video series: Introduction to machine learning with scikit-learn* - scikit-learn documentation: Cross-validation, Model evaluation - scikit-learn issue on GitHub: MSE is negative when returned by cross_val_score - Section 5.1 of An Introduction to Statistical Learning (11 pages) and related videos: K-fold and leave-one-out cross-validation (14 minutes), Cross-validation the right and wrong ways (10 minutes) - Scott Fortmann-Roe: Accurately Measuring Model Prediction Error - Machine Learning Mastery: An Introduction to Feature Selection - Harvard CS109: Cross-Validation: The Right and Wrong Way - Journal of Cheminformatics: Cross-validation pitfalls when selecting and assessing regression and classification models