

4-Copy1

September 30, 2018

1 Instructions

The following Cells need to be executed.

They are used to download and generate a dataset that has an aggregated count of bike trips per hundredth of an hour through the 24 hours in a day.

I put all this here instead of providing you the dataset directly, so that you could learn something along the way :)

The assignment is in the last cell.

```
In [1]: !pip3 install seaborn
```

```
Requirement already satisfied: seaborn in /usr/local/lib/python3.7/site-packages (0.9.0)
Requirement already satisfied: matplotlib>=1.4.3 in /usr/local/lib/python3.7/site-packages (from seaborn)
Requirement already satisfied: pandas>=0.15.2 in /usr/local/lib/python3.7/site-packages (from seaborn)
Requirement already satisfied: numpy>=1.9.3 in /usr/local/lib/python3.7/site-packages (from seaborn)
Requirement already satisfied: scipy>=0.14.0 in /usr/local/lib/python3.7/site-packages (from seaborn)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.7/site-packages (from matplotlib)
Requirement already satisfied: python-dateutil>=2.1 in /usr/local/lib/python3.7/site-packages (from pandas)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.7/site-packages (from matplotlib)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in /usr/local/lib/python3.7/site-packages (from matplotlib)
Requirement already satisfied: pytz>=2011k in /usr/local/lib/python3.7/site-packages (from pandas)
Requirement already satisfied: six in /usr/local/lib/python3.7/site-packages (from cycler>=0.10)
Requirement already satisfied: setuptools in /usr/local/lib/python3.7/site-packages (from kiwisolver)
```

1.1 This cell automatically downloads Capital Bikeshare data

```
In [2]: import pandas as pd
        bikes = pd.read_csv('../data/2016-Q1-Trips-History-Data.csv')
        bikes.head()
```

```
Out[2]:
```

	Duration (ms)	Start date	End date	Start station number	\
0	301295	3/31/2016 23:59	4/1/2016 0:04	31280	
1	557887	3/31/2016 23:59	4/1/2016 0:08	31275	
2	555944	3/31/2016 23:59	4/1/2016 0:08	31101	
3	766916	3/31/2016 23:57	4/1/2016 0:09	31226	
4	139656	3/31/2016 23:57	3/31/2016 23:59	31011	

	Start station	End station number	\
0	11th & S St NW	31506	
1	New Hampshire Ave & 24th St NW	31114	
2	14th & V St NW	31221	
3	34th St & Wisconsin Ave NW	31214	
4	23rd & Crystal Dr	31009	

	End station	Bike number	Member Type
0	1st & Rhode Island Ave NW	W00022	Registered
1	18th St & Wyoming Ave NW	W01294	Registered
2	18th & M St NW	W01416	Registered
3	17th & Corcoran St NW	W01090	Registered
4	27th & Crystal Dr	W21934	Registered

```
In [3]: # Placed the same script in a different cell to see what result this
# code yields
bikes['start'] = pd.to_datetime(bikes['Start date'], infer_datetime_format=True)
bikes['end'] = pd.to_datetime(bikes['End date'], infer_datetime_format=True)
bikes.head()

# It looks like the same information but in a different format
```

```
Out[3]:
```

	Duration (ms)	Start date	End date	Start station number	\
0	301295	3/31/2016 23:59	4/1/2016 0:04	31280	
1	557887	3/31/2016 23:59	4/1/2016 0:08	31275	
2	555944	3/31/2016 23:59	4/1/2016 0:08	31101	
3	766916	3/31/2016 23:57	4/1/2016 0:09	31226	
4	139656	3/31/2016 23:57	3/31/2016 23:59	31011	

	Start station	End station number	\
0	11th & S St NW	31506	
1	New Hampshire Ave & 24th St NW	31114	
2	14th & V St NW	31221	
3	34th St & Wisconsin Ave NW	31214	
4	23rd & Crystal Dr	31009	

	End station	Bike number	Member Type	start	\
0	1st & Rhode Island Ave NW	W00022	Registered	2016-03-31 23:59:00	
1	18th St & Wyoming Ave NW	W01294	Registered	2016-03-31 23:59:00	
2	18th & M St NW	W01416	Registered	2016-03-31 23:59:00	
3	17th & Corcoran St NW	W01090	Registered	2016-03-31 23:57:00	
4	27th & Crystal Dr	W21934	Registered	2016-03-31 23:57:00	

```
end
0 2016-04-01 00:04:00
1 2016-04-01 00:08:00
2 2016-04-01 00:08:00
```

```
3 2016-04-01 00:09:00
4 2016-03-31 23:59:00
```

1.1.1 Create a new column that represents the hour of the day

```
In [4]: # So, the hour of day is really concerning the starting timepoint of bikeshare uses
        bikes['hour_of_day'] = (bikes.start.dt.hour + (bikes.start.dt.minute/60).round(2))
```

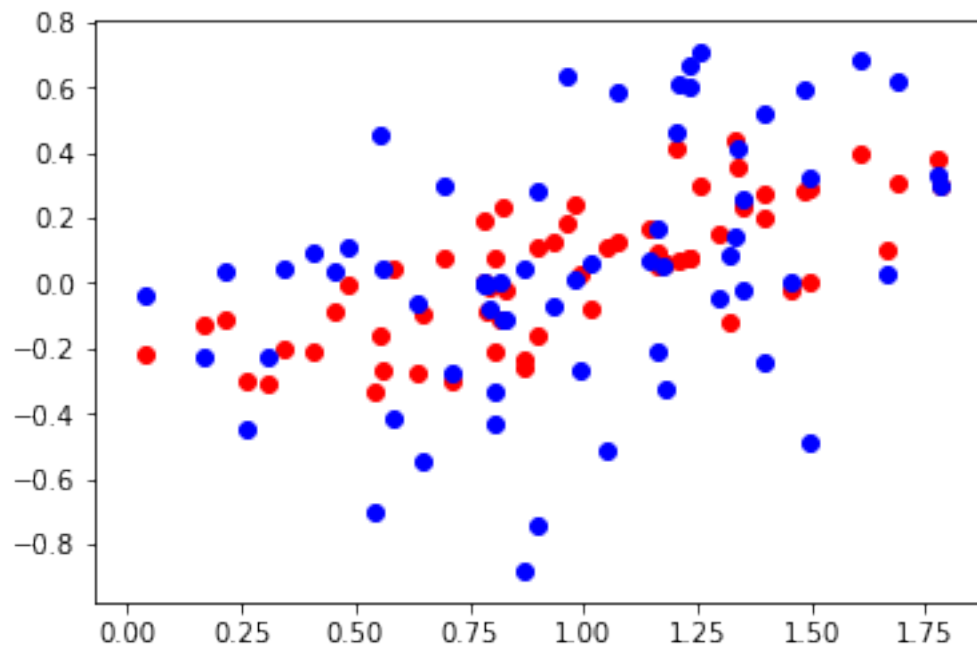
1.1.2 Aggregate to get a count per hour/minute of the day across all trips

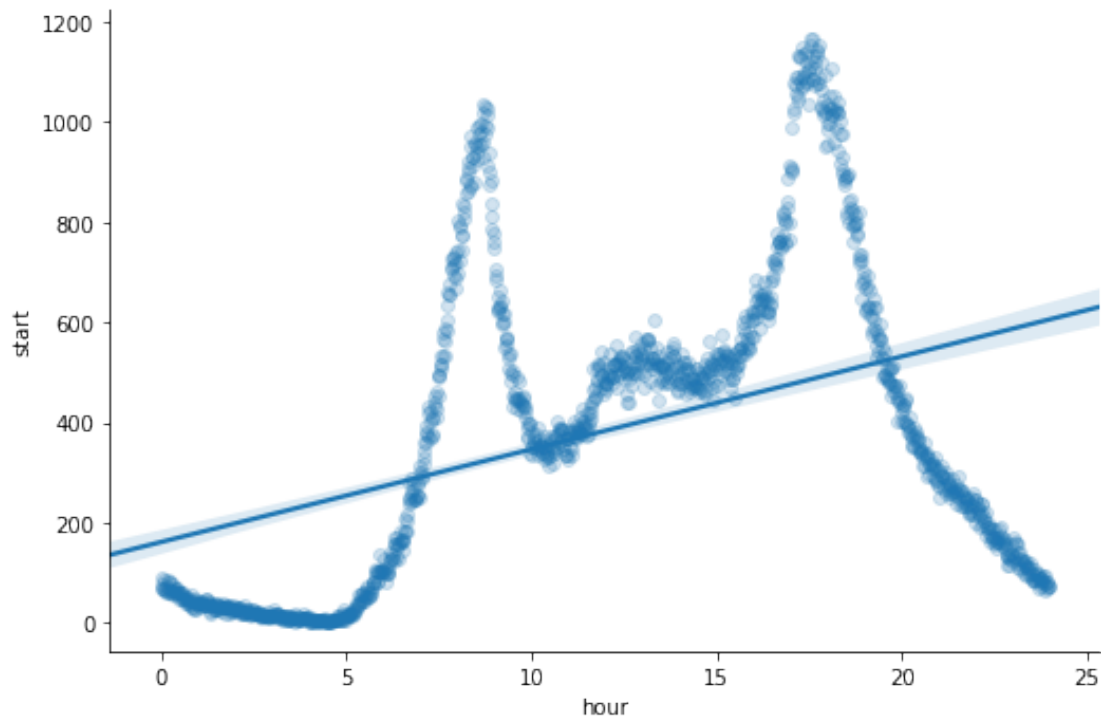
```
In [5]: import seaborn as sns
        import matplotlib.pyplot as plt
        %matplotlib inline

        # Aggregating the column dimension, then indexing it
        hours = bikes.groupby('hour_of_day').agg('count')
        hours['hour'] = hours.index

        # plotting the aggregate number
        hours.start.plot()
        sns.lmplot(x='hour', y='start', data=hours, aspect=1.5, scatter_kws={'alpha':0.2})
```

```
Out[5]: <seaborn.axisgrid.FacetGrid at 0x107d64cc0>
```





2 Assignment 4

Using the hours dataframe and the hour_of_day column, perform the following cells.

Explain the results in a **paragraph + charts** of to describe which model you'd recommend

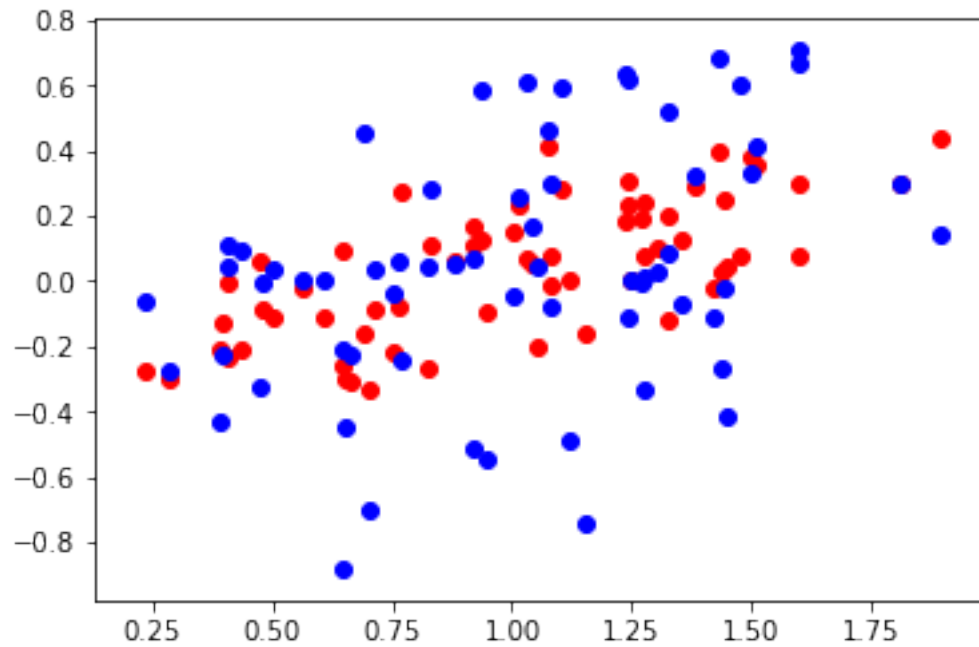
2.1 1. Create 3 models fit to hour_of_day with varying polynomial degrees

```
In [6]: # I'm following along your Loss Function Comparison File
        from sklearn import linear_model # adding additional module not already listed from above

        # I prefer not using x and y as names
        x_times = hours[['hour']]
        y_starting = hours.start

        plt.scatter(x_times, y_starting)
```

Out[6]: <matplotlib.collections.PathCollection at 0x108644e48>

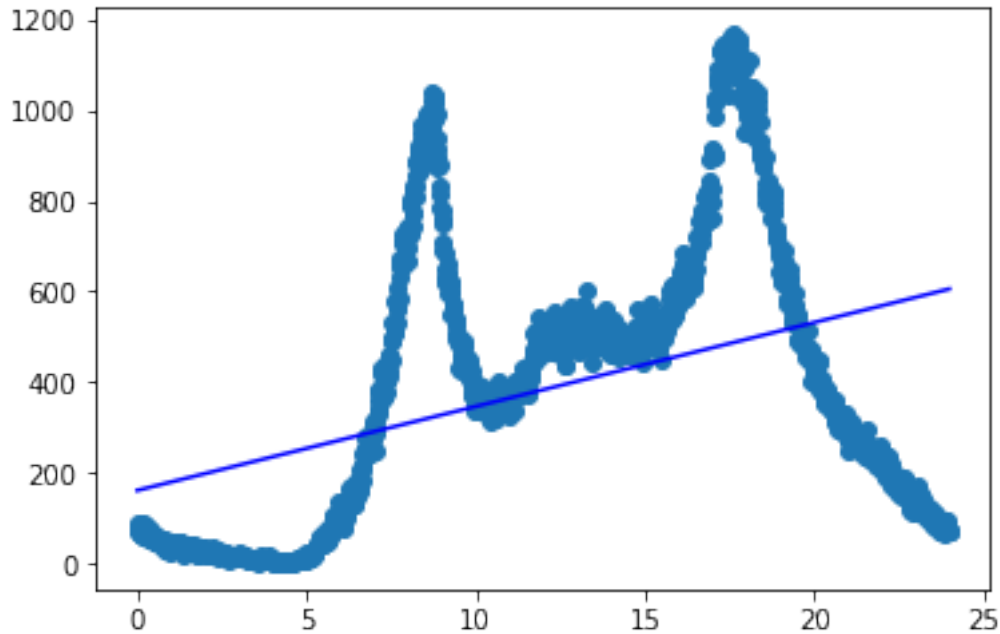


```
In [7]: # For my reference - Setting up regular linear regresssion
        from sklearn.linear_model import LinearRegression

        linear = LinearRegression()
        linear.fit(x_times, y_starting)

        # Plotting
        plt.scatter(x_times, y_starting)
        plt.plot(x_times, x_times*linear.coef_ + linear.intercept_, c = "b" )

Out[7]: [<matplotlib.lines.Line2D at 0x108ebbc18>]
```



```
In [8]: # Model 1, polynomial linear regression x25 degree
from sklearn.preprocessing import PolynomialFeatures

poly_25 = PolynomialFeatures(degree=25)
x_25 = poly_25.fit_transform(x_times) # got rid of .reshape
x_25
```

```
Out[8]: array([[1.00000000e+00, 0.00000000e+00, 0.00000000e+00, ...,
                0.00000000e+00, 0.00000000e+00, 0.00000000e+00],
               [1.00000000e+00, 2.00000000e-02, 4.00000000e-04, ...,
                8.38860800e-40, 1.67772160e-41, 3.35544320e-43],
               [1.00000000e+00, 3.00000000e-02, 9.00000000e-04, ...,
                9.41431788e-36, 2.82429536e-37, 8.47288609e-39],
               ...,
               [1.00000000e+00, 2.39500000e+01, 5.73602500e+02, ...,
                5.29696262e+31, 1.26862255e+33, 3.03835100e+34],
               [1.00000000e+00, 2.39700000e+01, 5.74560900e+02, ...,
                5.39963971e+31, 1.29429364e+33, 3.10242185e+34],
               [1.00000000e+00, 2.39800000e+01, 5.75040400e+02, ...,
                5.45168949e+31, 1.30731514e+33, 3.13494170e+34]])
```

```
In [9]: linear = linear_model.LinearRegression()
linear.fit(x_25, y_starting)
linear.coef_, linear.intercept_

# So far just copy and pasting
```

```
Out[9]: (array([-4.70053389e-21,  4.25577597e-19,  2.86340819e-22, -2.87151676e-25,
                1.52942891e-27,  2.27110474e-30,  2.04295496e-30,  2.37799436e-29,
                2.78276140e-28,  3.21951564e-27,  3.65473938e-26,  4.03725517e-25,
                4.29819285e-24,  4.35744774e-23,  4.14022223e-22,  3.60547568e-21,
                2.78224971e-20,  1.79851813e-19,  8.73208023e-19,  2.38526543e-18,
                -5.17154209e-19,  4.14076916e-20, -1.45700494e-21,  1.47044652e-23,
                3.45890175e-25, -7.07597579e-27]), 273.72942946950593)
```

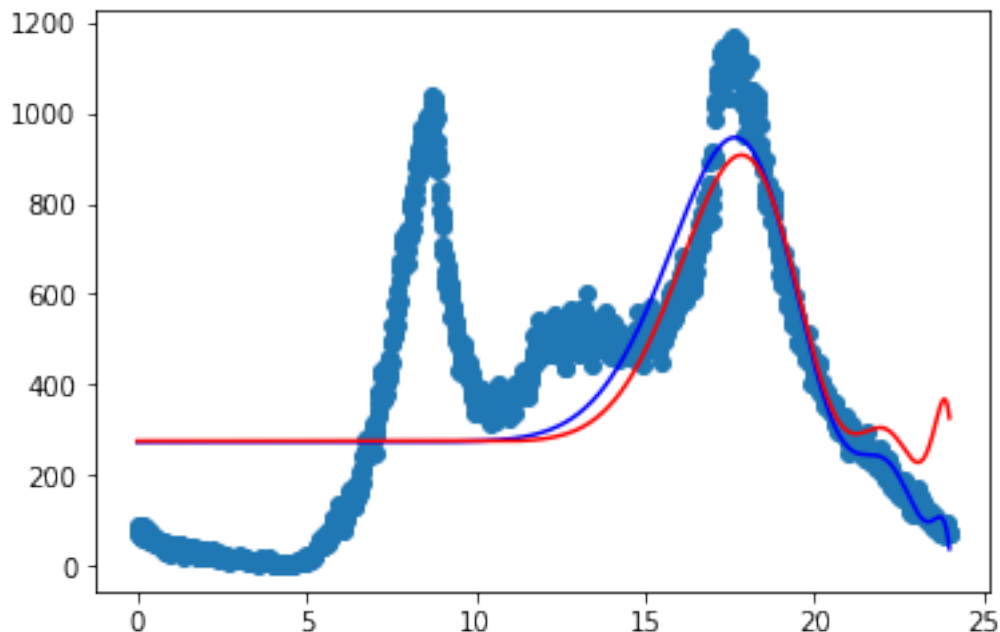
```
In [10]: ridge = linear_model.Ridge()
         ridge.fit(x_25, y_starting)
         ridge.coef_, ridge.intercept_
```

```
Out[10]: (array([-9.82678123e-18,  2.38239504e-16,  1.41333181e-16,  2.66195958e-16,
                6.35468615e-17, -4.56806931e-17,  5.84980919e-18,  2.96815590e-18,
                -4.81236845e-17,  5.85990452e-17,  8.27015192e-17,  8.41027834e-17,
                1.07612985e-16,  1.25774171e-16, -5.43810832e-17, -1.01639415e-16,
                -1.38116955e-18,  3.12792320e-17, -1.23109784e-16,  3.78594551e-17,
                -4.94899947e-18,  3.47754823e-19, -1.40282240e-20,  3.19538425e-22,
                -3.67705795e-24,  1.50466242e-26]), 275.45907916227975)
```

```
In [11]: # Model 1 : 25
         import numpy as np # I didn't need to until now

         plt.scatter(x_times, y_starting)
         plt.plot(x_times, np.dot(x_25, linear.coef_) + linear.intercept_, c='b')
         plt.plot(x_times, np.dot(x_25, ridge.coef_) + ridge.intercept_, c='r')
```

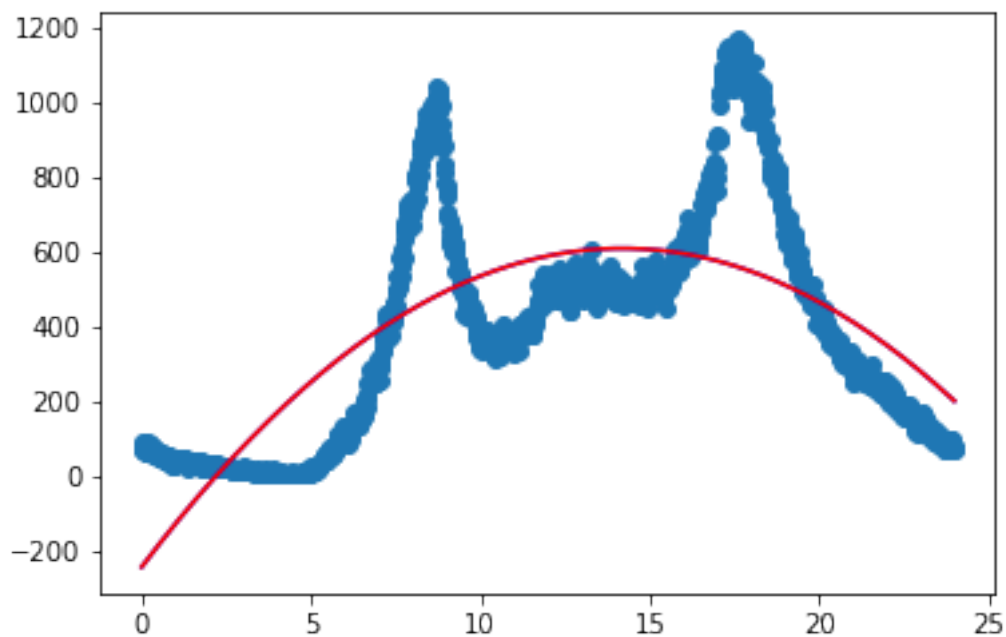
```
Out[11]: [<matplotlib.lines.Line2D at 0x108f1ee48>]
```



```
In [12]: # Okay.... I wasn't expecting that, but THAT IS COOL!  
# I will be using this for work most likely
```

```
In [13]: # Model 2, polynomial linear regression x2 degree  
# More concise this time.  
poly_2 = PolynomialFeatures(degree=2)  
x_2 = poly_2.fit_transform(x_times) # got rid of .reshape  
linear.fit(x_2, y_starting)  
ridge.fit(x_2, y_starting)  
  
plt.scatter(x_times, y_starting)  
plt.plot(x_times, np.dot(x_2, linear.coef_) + linear.intercept_, c='b')  
plt.plot(x_times, np.dot(x_2, ridge.coef_) + ridge.intercept_, c='r')
```

```
Out[13]: [<matplotlib.lines.Line2D at 0x1090635c0>]
```



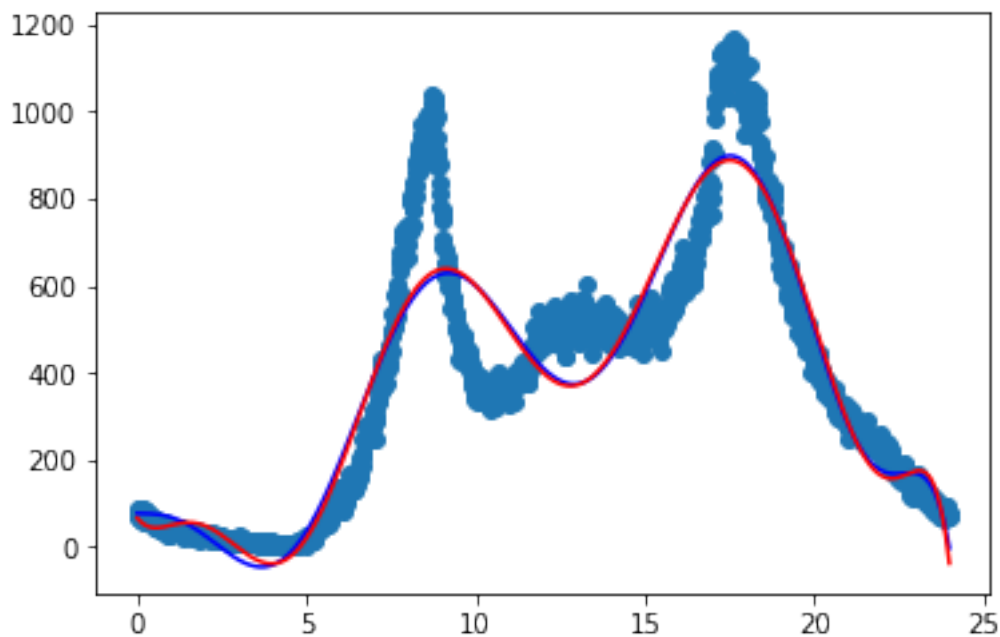
```
In [14]: # Model 3, polynomial linear regression x12 degree  
poly_12 = PolynomialFeatures(degree=12)  
x_12 = poly_12.fit_transform(x_times) # got rid of .reshape  
linear.fit(x_12, y_starting)  
ridge.fit(x_12, y_starting)  
  
plt.scatter(x_times, y_starting)
```



```
plt.plot(x_times, np.dot(x_12, linear.coef_) + linear.intercept_, c='b')
plt.plot(x_times, np.dot(x_12, ridge.coef_) + ridge.intercept_, c='r')
```

```
/Users/dell/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/ridge.py:112: LinAlgWarni
Ill-conditioned matrix detected. Result is not guaranteed to be accurate.
Reciprocal condition number1.474511e-35
  overwrite_a=True).T
```

Out[14]: [



```
In [15]: # I want to see what will happen if I added more data points like you
# had in the Loss Function Comparison file. But, adding more fake data
# points here would not have the same meaning. While we've already known
# how the scatterplot will look in the Loss Function Comparison file,
# adding more points after 24 hours doesn't make sense. That'll be
# like breaking the law of physics or going against social conventions of
# measuring time.

# In Model 1, it appears that the linear method appears to follow
# along the datapoints at the x=24 mark while the ridge method "refuses"
# to fall down the slope. This is a good thing. I will explain in a sec.
# In the second and third model, both linear and ridge lines are traveling
# more-or-less the same trajectory.

# In determining which model would be the best recommendation, I have
```

*# been thinking about the context of the graphs. For example, although I
 # really like how the third model glides along the spiked datapoints,
 # the predictive direction appears to take about a dramatic end. And,
 # the question I should be asking at this point is - what does this mean
 # in the context of the graph drawn?*

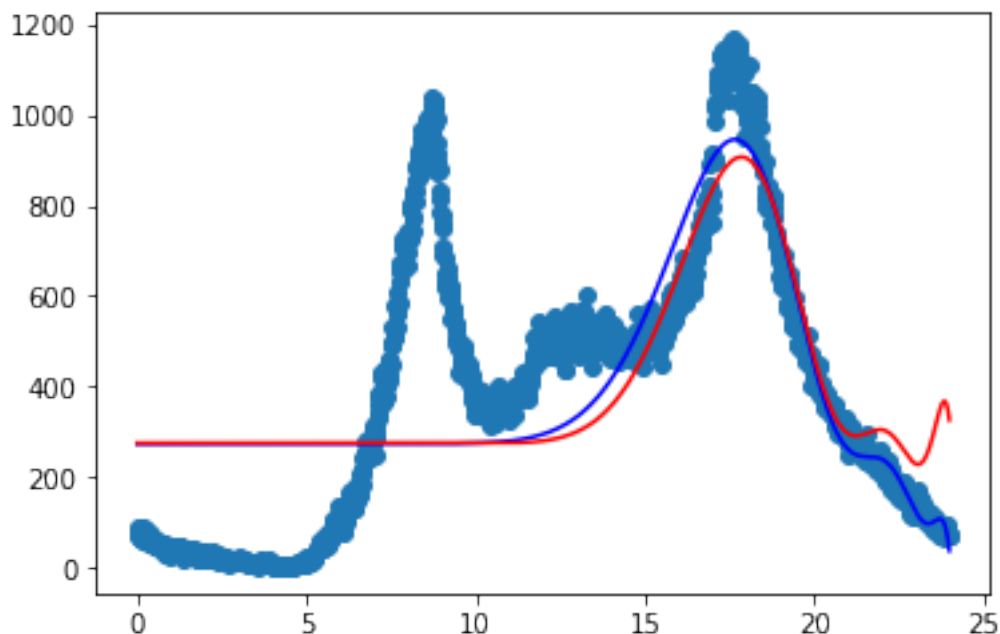
*# After 24 hours, the clock will circle back to 0. We already know the
 # value of y at x = 0. If we wanted to predict something, then
 # we would have to revisit x = 0 rather than asking the
 # value of y after 24. I don't think Model 2 really gives us
 # any useful information other than reflecting an increase and decrease
 # of trend. Finally, we are left with Model 1, where the ridge method,
 # as mentioned above, "refuses" to fall down the spike. But, earlier
 # times' trajectories appear to be producing high residuals.*

2.2 2. Choose one of the polynomial models and create 3 new models fit to hour_of_day with different Ridge Regression α (alpha) Ridge Coefficient values

```
In [16]: # Model 1, polynomial linear regression x25 degree + alpha = .1
linear.fit(x_25, y_starting)
ridge1 = linear_model.Ridge(alpha = .1)
ridge1.fit(x_25, y_starting)

plt.scatter(x_times, y_starting)
plt.plot(x_times, np.dot(x_25, linear.coef_) + linear.intercept_, c='b')
plt.plot(x_times, np.dot(x_25, ridge1.coef_) + ridge1.intercept_, c='r')
```

Out[16]: [matplotlib.lines.Line2D at 0x109b61c88>]



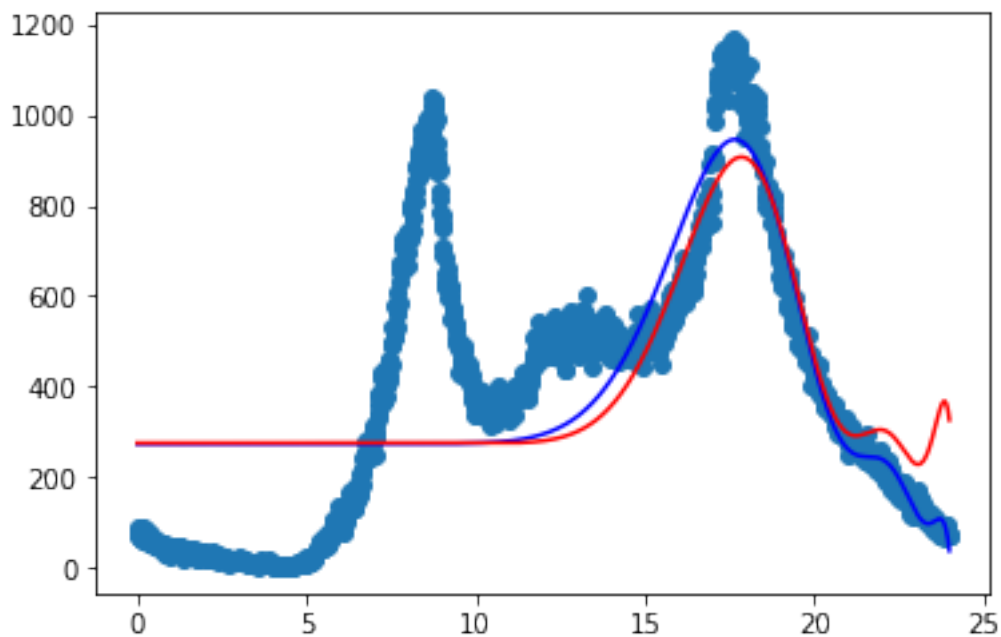
```

In [17]: # Model 2, polynomial linear regression x25 degree + alpha = .5
linear.fit(x_25, y_starting)
ridge2 = linear_model.Ridge(alpha = .5)
ridge2.fit(x_25, y_starting)

plt.scatter(x_times, y_starting)
plt.plot(x_times, np.dot(x_25, linear.coef_) + linear.intercept_, c='b')
plt.plot(x_times, np.dot(x_25, ridge2.coef_) + ridge2.intercept_, c='r')

```

Out[17]: [



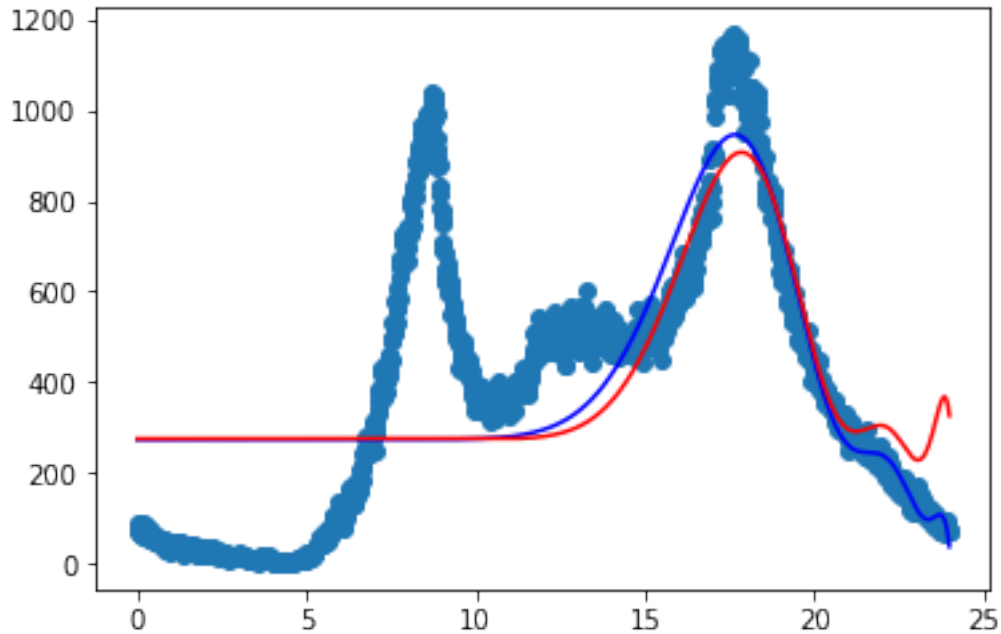
```

In [18]: # Model 3, polynomial linear regression x25 degree + alpha = 20
linear.fit(x_25, y_starting)
ridge3 = linear_model.Ridge(alpha = 20)
ridge3.fit(x_25, y_starting)

plt.scatter(x_times, y_starting)
plt.plot(x_times, np.dot(x_25, linear.coef_) + linear.intercept_, c='b')
plt.plot(x_times, np.dot(x_25, ridge3.coef_) + ridge3.intercept_, c='r')

```

Out[18]: [



```
In [19]: # Changing the alpha values do not appear to induce any change
# to graph illustrations. So, I wanted to find out if the values were
# infact changing when alphas changed
```

```
# Checking to see if this compare method would work to test alphas
```

```
from IPython.display import display
```

```
same_A = 1
```

```
same_B = 1
```

```
display(same_A is same_B)
```

```
diff_A = 1
```

```
diff_B = 2
```

```
display(diff_A is diff_B)
```

True

False

```
In [20]: # Above method worked, so I'm going to use it to test alphas
```

```
# Control
```

```
ridge_pointOne = linear_model.Ridge(alpha=.1)
```

```
ridge_A = ridge_pointOne.fit(x_25, y_starting)
```

```
ridge_B = ridge_pointOne.fit(x_25, y_starting)
```

```

display(ridge_A is ridge_B)

# Different alphas
ridge1 = linear_model.Ridge(alpha=.1)
ridge2 = linear_model.Ridge(alpha=.5)
ridge3 = linear_model.Ridge(alpha=20)

ridge_1 = ridge1.fit(x_25, y_starting)
ridge_2 = ridge2.fit(x_25, y_starting)
ridge_3 = ridge3.fit(x_25, y_starting)

display(ridge_1 is ridge_2)
display(ridge_1 is ridge_3)
display(ridge_2 is ridge_3)

```

True

False

False

False

In [21]: *# I'm wondering if I've done something wrong. So, I'm printing graphs for another degree*

```

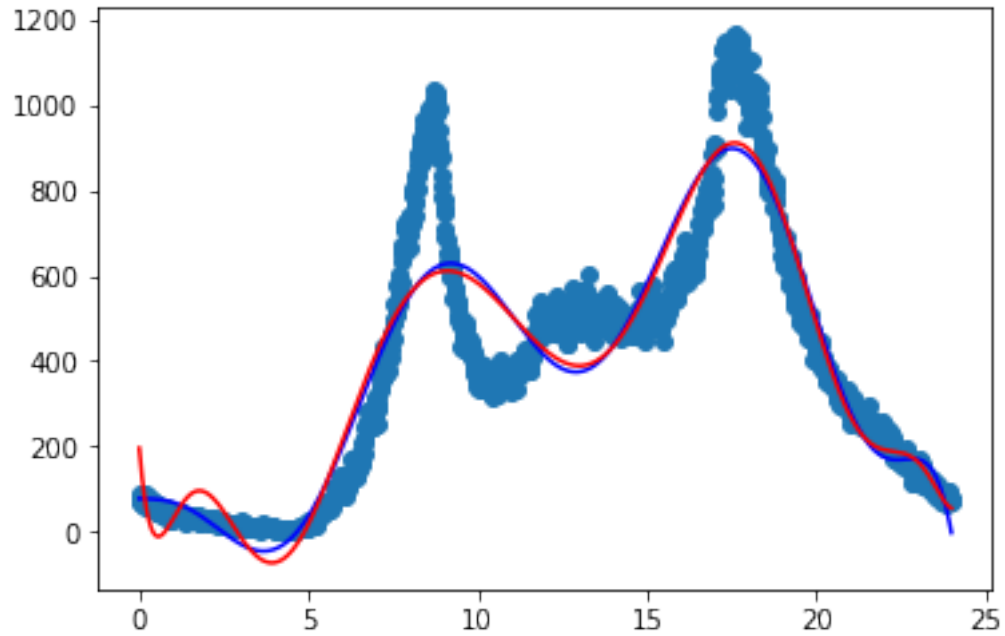
linear.fit(x_12, y_starting)
ridge1 = linear_model.Ridge(alpha = .1)
ridge1.fit(x_12, y_starting)

plt.scatter(x_times, y_starting)
plt.plot(x_times, np.dot(x_12, linear.coef_) + linear.intercept_, c='b')
plt.plot(x_times, np.dot(x_12, ridge1.coef_) + ridge1.intercept_, c='r')

```

/Users/dell/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/ridge.py:112: LinAlgWarning
Ill-conditioned matrix detected. Result is not guaranteed to be accurate.
Reciprocal condition number1.320701e-36
 overwrite_a=True).T

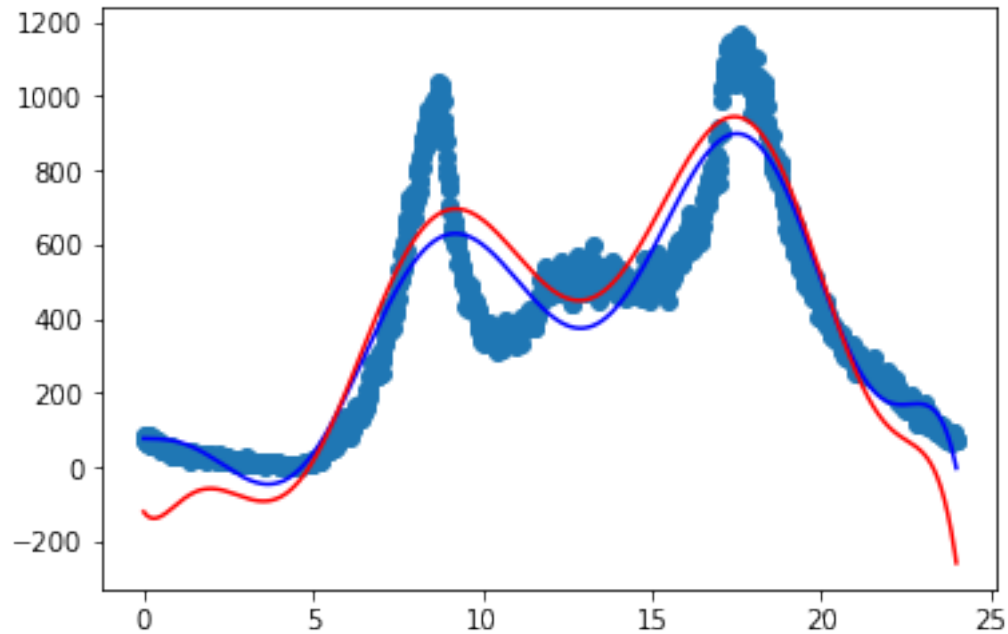
Out[21]: [



```
In [22]: linear.fit(x_12, y_starting)
         ridge1 = linear_model.Ridge(alpha = .5)
         ridge1.fit(x_12, y_starting)

         plt.scatter(x_times, y_starting)
         plt.plot(x_times, np.dot(x_12, linear.coef_) + linear.intercept_, c='b')
         plt.plot(x_times, np.dot(x_12, ridge1.coef_) + ridge1.intercept_, c='r')
```

```
Out [22]: [<matplotlib.lines.Line2D at 0x109e33358>]
```



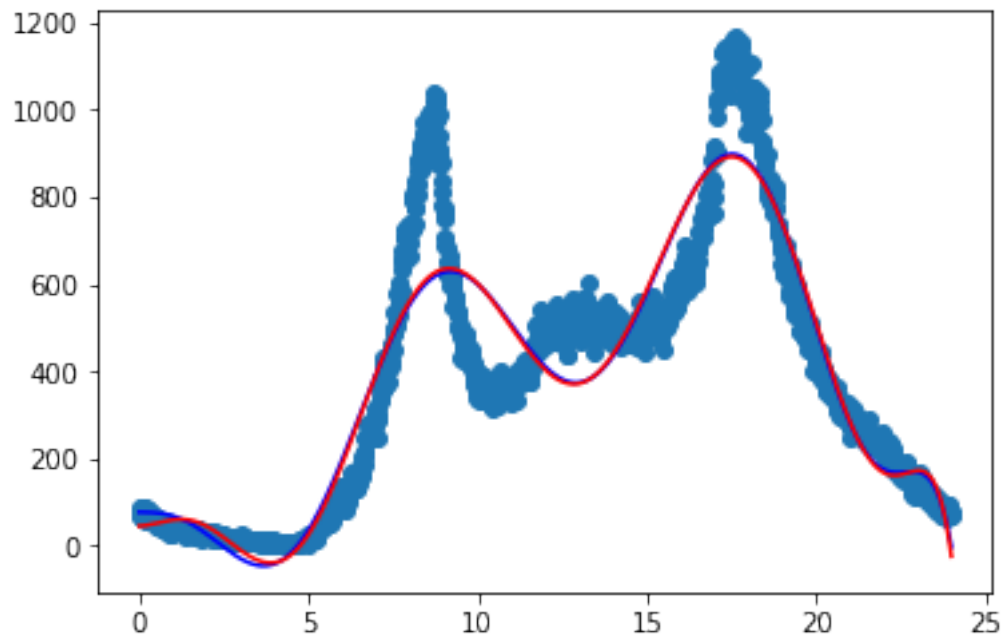
```
In [23]: linear.fit(x_12, y_starting)
         ridge1 = linear_model.Ridge(alpha = 20)
         ridge1.fit(x_12, y_starting)
```

```
plt.scatter(x_times, y_starting)
plt.plot(x_times, np.dot(x_12, linear.coef_) + linear.intercept_, c='b')
plt.plot(x_times, np.dot(x_12, ridge1.coef_) + ridge1.intercept_, c='r')
```

```
/Users/dell/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/ridge.py:112: LinAlgWarning:
Ill-conditioned matrix detected. Result is not guaranteed to be accurate.
```

```
Reciprocal condition number2.512771e-34
      overwrite_a=True).T
```

```
Out[23]: [<matplotlib.lines.Line2D at 0x10d02a860>]
```



In [24]: *# So, it's not my method that's wrong. x25 does produce very similar
looking graphs regardless the alpha value*