We read in the data

In [72]:
```
import matplotlib.pyplot as plt
%matplotlib inline
plt.rcParams['figure.figsize'] = 20, 10
import pandas as pd
import numpy as np
from sklearn import linear_model, metrics

day_hour_count = pd.read_csv("bikeshare_hour_count.csv")
day_hour_count
```

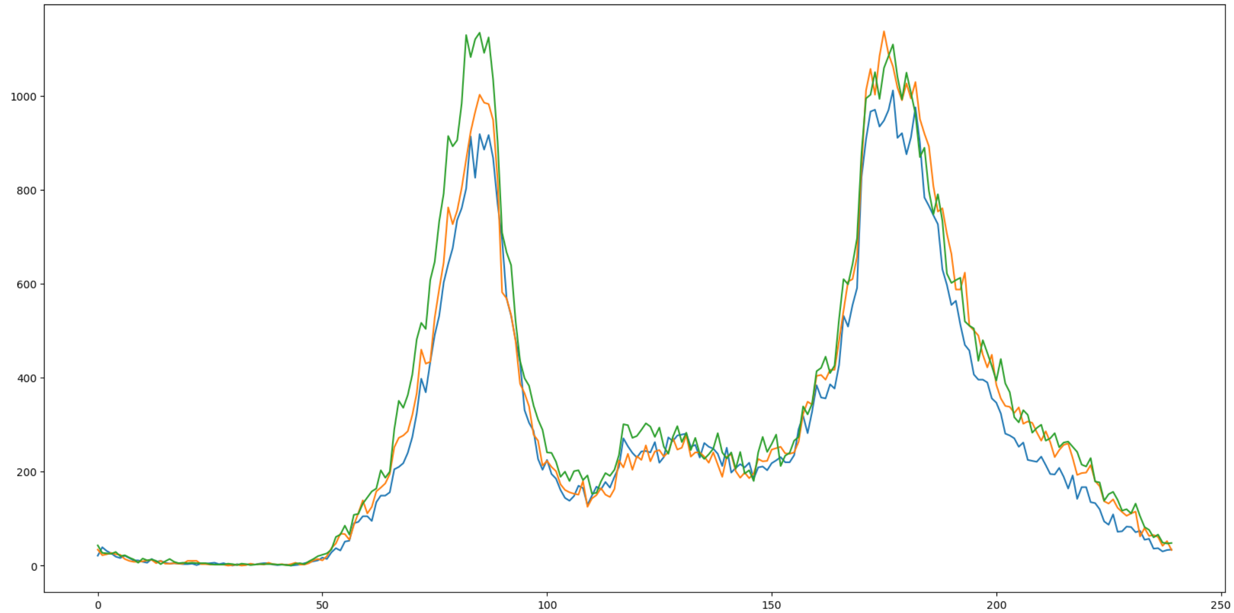
Out[72]:

	hour	monday	tuesday	wednesday	thursday	friday	saturday	sunday
0	0.0	21	34	43	47	51	89	106
1	0.1	39	22	27	37	56	87	100
2	0.2	31	24	26	42	50	98	77
3	0.3	26	27	25	29	52	99	87
4	0.4	19	24	29	29	50	98	69
...	...	...	...	...	...	...	...	...
235	23.5	36	65	60	94	80	93	28
236	23.6	37	61	66	100	81	95	28
237	23.7	30	42	49	80	101	105	27
238	23.8	33	52	47	79	91	93	24
239	23.9	34	33	48	65	105	111	23

240 rows × 8 columns

In [73]:
```
plt.figure(figsize=(20,10))
plt.plot(day_hour_count.index, day_hour_count["monday"])
plt.plot(day_hour_count.index, day_hour_count["tuesday"])
plt.plot(day_hour_count.index, day_hour_count["wednesday"])
```

Out[73]:
```
[<matplotlib.lines.Line2D at 0x121a0d2f6a0>]
```



Assignment 4

Explain the results in a **paragraph + charts** of to describe which model you'd recommend. This means show the data and the model's line on the same chart. The paragraph is a simple justification and comparison of the several models you tried.

1. Using the `day_hour_count` dataframe create 4 dataframes `monday`, `tuesday`, `saturday` and `sunday` that represent the data for those days. (hint: Monday is day=0)

In [74]:
```
monday = day_hour_count[["hour","monday"]].copy()
```

In [75]:
```
tuesday = day_hour_count[["hour","tuesday"]].copy()
```

In [76]:
```
saturday = day_hour_count[["hour","saturday"]].copy()
```

In [77]:
```
sunday = day_hour_count[["hour","sunday"]].copy()
```

In [78]:
```
monday
```

Out[78]:

	hour	monday
0	0.0	21
1	0.1	39
2	0.2	31
3	0.3	26
4	0.4	19
...	...	...
235	23.5	36
236	23.6	37
237	23.7	30
238	23.8	33
239	23.9	34

240 rows × 2 columns

In [79]:
```
tuesday
```

Out[79]:

	hour	tuesday
0	0.0	34
1	0.1	22
2	0.2	24
3	0.3	27
4	0.4	24
...	...	...
235	23.5	65
236	23.6	61
237	23.7	42
238	23.8	52
239	23.9	33

240 rows × 2 columns

In [80]:
```
saturday
```

Out[80]:

	hour	saturday
0	0.0	89
1	0.1	87
2	0.2	98
3	0.3	99
4	0.4	98
...	...	...
235	23.5	93
236	23.6	95
237	23.7	105
238	23.8	93
239	23.9	111

240 rows × 2 columns

In [81]:

```
sunday
```

Out[81]:

	hour	sunday
0	0.0	106
1	0.1	100
2	0.2	77
3	0.3	87
4	0.4	69
...	...	...
235	23.5	28
236	23.6	28
237	23.7	27
238	23.8	24
239	23.9	23

240 rows × 2 columns

2a. Create 3 models fit to (`x=hour`, `y=monday`) with varying polynomial degrees (choose from `n=5,15,20`). (Repeat for `saturday` below)

Plot all the results for each polynomial.

In [84]:
```
from sklearn.preprocessing import PolynomialFeatures

hour = monday.hour.values.reshape(-1,1)
mon = monday.monday.values.reshape(-1,1)

poly5 = PolynomialFeatures(degree = 5)
poly15 = PolynomialFeatures(degree = 15)
poly20 = PolynomialFeatures(degree = 20)

mon_5 = poly5.fit_transform(hour)
mon_15 = poly15.fit_transform(hour)
mon_20 = poly20.fit_transform(hour)

linear = linear_model.LinearRegression()
linear.fit(hour, mon)
```

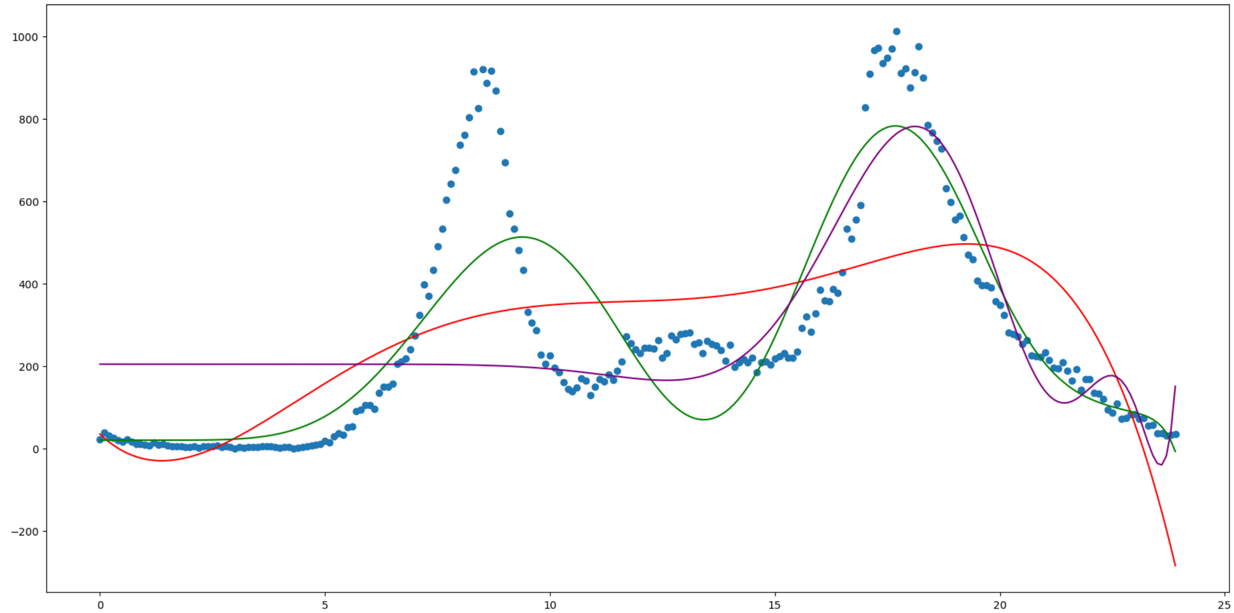
Out[84]:
```
▾ LinearRegression
LinearRegression()
```

In [87]:
```
mon_lin_5 = linear_model.LinearRegression()
mon_lin_15 = linear_model.LinearRegression()
mon_lin_20 = linear_model.LinearRegression()

mon_lin_5.fit(mon_5, mon)
mon_lin_15.fit(mon_15, mon)
mon_lin_20.fit(mon_20, mon)

(mon_lin_5.coef_, linear.intercept_)
(mon_lin_15.coef_, linear.intercept_)
(mon_lin_20.coef_, linear.intercept_)
```

Out[87]:
```
(array([[ 0.00000000e+00, -1.65658278e-14,  2.02122306e-18,
          1.42417102e-20, -6.38181145e-21, -7.15191371e-20,
         -7.81712934e-19, -8.17580759e-18, -8.10853993e-17,
         -7.51834408e-16, -6.37985192e-15, -4.79294291e-14,
         -3.01416655e-13, -1.42195086e-12, -3.75437161e-12,
          9.95460278e-13, -1.00391565e-13,  4.96769788e-15,
         -1.21535205e-16,  1.18230350e-18, -8.67719959e-23]]),
 array([114.23817427]))
```

In [89]:
```
plt.scatter(monday.hour, monday.monday)
plt.plot(hour, mon_lin_5.predict(mon_5), c = 'red')
plt.plot(hour, mon_lin_15.predict(mon_15), c = 'green')
plt.plot(hour, mon_lin_20.predict(mon_20), c = 'purple')
```

Out[89]:
```
[<matplotlib.lines.Line2D at 0x121a0e6dd20>]
```



Model 2 (green) or the polynomial model with 15 variables. The 5 variable polynomial doesn't fit closely enough to the data with all of the curves. Contrary to the smaller polynomial, the largest one, the 20 variable, takes too many curves near the end and beginning with the more concentrated data points. The 15 degree polynomial takes the "just right" route of moving along the same curve without too high of concentration at any one point. It also has the smallest MSE out of the 3 models. (See below.)

In [137…

```
(
metrics.mean_squared_error(mon[-4:], mon_lin_5.predict(mon_5[-4:])),
metrics.mean_squared_error(mon[-4:], mon_lin_15.predict(mon_15[-4:])),
metrics.mean_squared_error(mon[-4:], mon_lin_20.predict(mon_20[-4:]))
)
```

Out[137]:

```
(65890.53913904465, 561.8264252961378, 5502.914493822458)
```

2b. Repeat `2a` for `saturday`

In [96]:

```
sat = saturday.saturday.values.reshape(-1,1)

sat_5 = poly5.fit_transform(hour)
sat_15 = poly15.fit_transform(hour)
sat_20 = poly20.fit_transform(hour)

linear = linear_model.LinearRegression()
linear.fit(hour, sat)
```

Out[96]:

```
▾ LinearRegression
LinearRegression()
```

In [97]:

```
sat_lin_5 = linear_model.LinearRegression()
sat_lin_15 = linear_model.LinearRegression()
sat_lin_20 = linear_model.LinearRegression()

sat_lin_5.fit(sat_5, sat)
sat_lin_15.fit(sat_15, sat)
sat_lin_20.fit(sat_20, sat)

(sat_lin_5.coef_, linear.intercept_)
(sat_lin_15.coef_, linear.intercept_)
(sat_lin_20.coef_, linear.intercept_)
```

Out[97]:

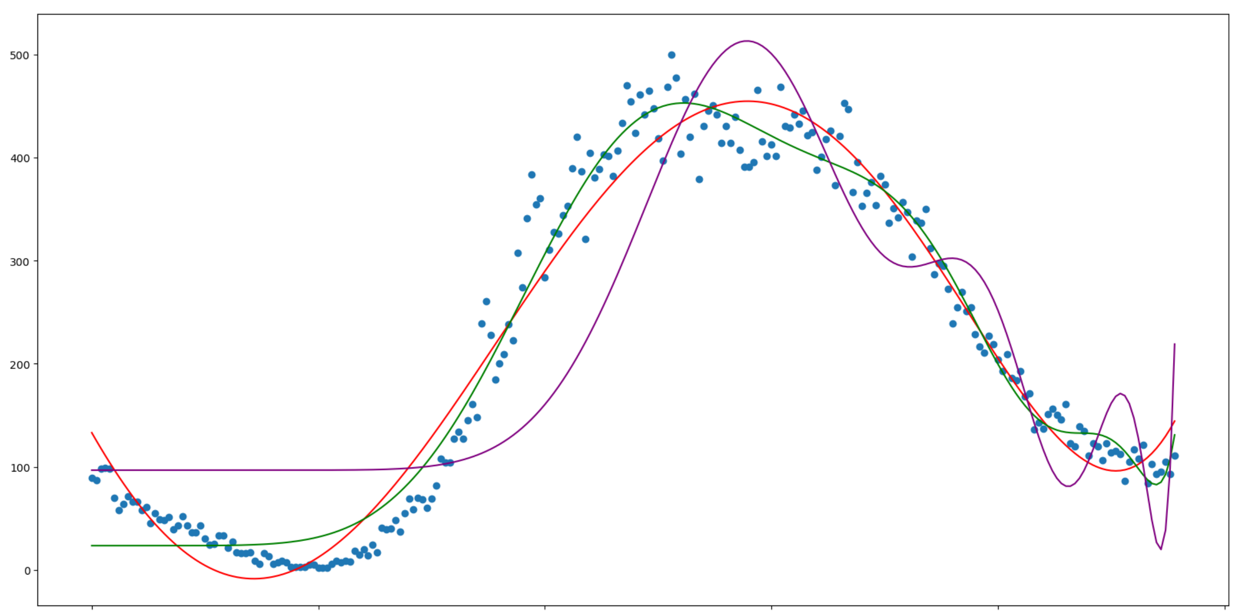
```
(array([[ 0.00000000e+00,  1.30326314e-13, -1.58725803e-17,
         -1.11944581e-19,  5.01858820e-20,  5.62345660e-19,
          6.14567767e-18,  6.42657858e-17,  6.37231794e-16,
          5.90678169e-15,  5.01028478e-14,  3.76173043e-13,
          2.36322785e-12,  1.11253983e-11,  2.91819918e-11,
         -9.00284181e-12,  1.10626709e-12, -7.16114797e-14,
          2.59158550e-15, -4.98141622e-17,  3.97646141e-19]]),
 array([91.97282158]))
```

In [98]:

```
plt.scatter(saturday.hour, saturday.saturday)
plt.plot(hour, sat_lin_5.predict(sat_5), c = 'red')
plt.plot(hour, sat_lin_15.predict(sat_15), c = 'green')
plt.plot(hour, sat_lin_20.predict(sat_20), c = 'purple')
```

Out[98]:

```
[<matplotlib.lines.Line2D at 0x121a0f87250>]
```



3. Similar to Monday's models, out of Saturday's models, the 15 degree polynomial is the best fit to the data and has the least MSE to the true data. It doesn't

take unessary dips and jumps with every small curve in the data, but still moves with the patterns.

In [138…

```
(
metrics.mean_squared_error(sat[-4:], sat_lin_5.predict(sat_5[-4:])),
metrics.mean_squared_error(sat[-4:], sat_lin_15.predict(sat_15[-4:])),
metrics.mean_squared_error(sat[-4:], sat_lin_20.predict(sat_20[-4:]))
)
```

Out[138]:

```
(1109.1255203207406, 212.79900076571732, 5451.570151154124)
```

3. Using the best `monday` model's prediction, determine the errors (MSE, MAE, MAPE) between the prediction with the `monday` and `tuesday` datasets

Repeat for `saturday` / `sunday`

In [110…

```
#Monday/Tuesday
(
metrics.mean_squared_error(mon[-4:], mon_lin_15.predict(mon_15[-4:])),
metrics.mean_absolute_error(mon[-4:], mon_lin_15.predict(mon_15[-4:])),
metrics.mean_absolute_percentage_error(mon[-4:], mon_lin_15.predict(mon_15[-4:]))
)
```

Out[110]:

```
(561.8264252961378, 19.794336557388306, 0.5841382371315109)
```

In [111…

```
tue = tuesday.tuesday.values.reshape(-1,1)
(
metrics.mean_squared_error(tue[-4:], mon_lin_15.predict(mon_15[-4:])),
metrics.mean_absolute_error(tue[-4:], mon_lin_15.predict(mon_15[-4:])),
metrics.mean_absolute_percentage_error(tue[-4:], mon_lin_15.predict(mon_15[-4:]))
)
```

Out[111]:

```
(723.1544148743849, 21.903178930282593, 0.5326574954947045)
```

In [112…

```
#Saturday/Sunday
(
metrics.mean_squared_error(sat[-4:], sat_lin_15.predict(sat_15[-4:])),
metrics.mean_absolute_error(sat[-4:], sat_lin_15.predict(sat_15[-4:])),
metrics.mean_absolute_percentage_error(sat[-4:], sat_lin_15.predict(sat_15[-4:]))
)
```

Out[112]:

```
(212.79900076571732, 14.111837923526764, 0.1386742003946307)
```

In [113…

```
sun = sunday.sunday.values.reshape(-1,1)
(
metrics.mean_squared_error(sun[-4:], sat_lin_15.predict(sat_15[-4:])),
metrics.mean_absolute_error(sun[-4:], sat_lin_15.predict(sat_15[-4:])),
metrics.mean_absolute_percentage_error(sun[-4:], sat_lin_15.predict(sat_15[-4:]))
)
```

Out[113]: (6533.727641015091, 78.45328197181226, 3.156919231013168)

4. With `saturday`, use `train_test_split` to create training and test sets and build a model. Create predictions using the xtest from and determine the errors between these predictions and the ytest (MSE, MAE, MAPE).

repeat for `monday`

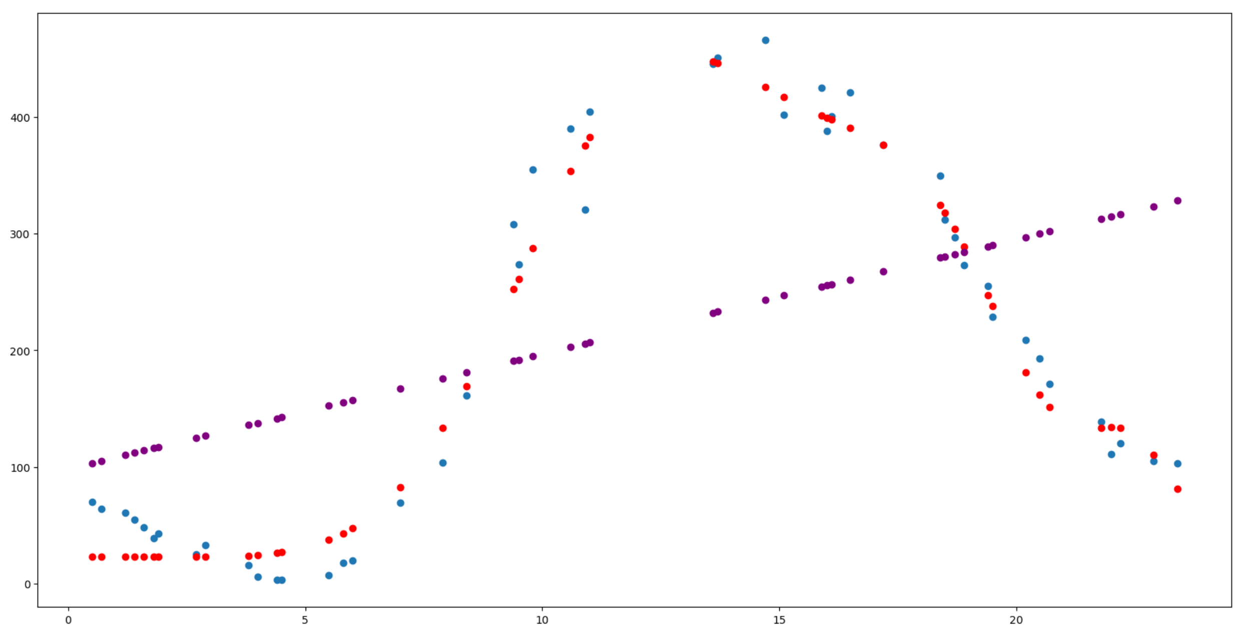
In [115…
```
from sklearn.model_selection import train_test_split
```

In [125…
```
#Saturday
xtrain, xtest, ytrain, ytest = train_test_split(hour, sat, test_size = 0.2)
linear = linear_model.LinearRegression().fit(xtrain, ytrain)
```

In [126…
```
xtrain15 = PolynomialFeatures(degree = 15).fit_transform(xtrain)
xtest15 = PolynomialFeatures(degree = 15).fit_transform(xtest)

linear15 = linear_model.LinearRegression().fit(xtrain15, ytrain)
```

In [131…
```
plt.scatter(xtest, ytest)
plt.scatter(xtest, linear15.predict(xtest15), c = 'red')
plt.scatter(xtest, linear.predict(xtest), c = 'purple')
```

Out[131]: <matplotlib.collections.PathCollection at 0x121a861b7f0>



In [132…
```
(
metrics.mean_squared_error(ytest, linear15.predict(xtest15)),
metrics.mean_absolute_error(ytest, linear15.predict(xtest15)),
metrics.mean_absolute_percentage_error(ytest, linear15.predict(xtest15))
)
```

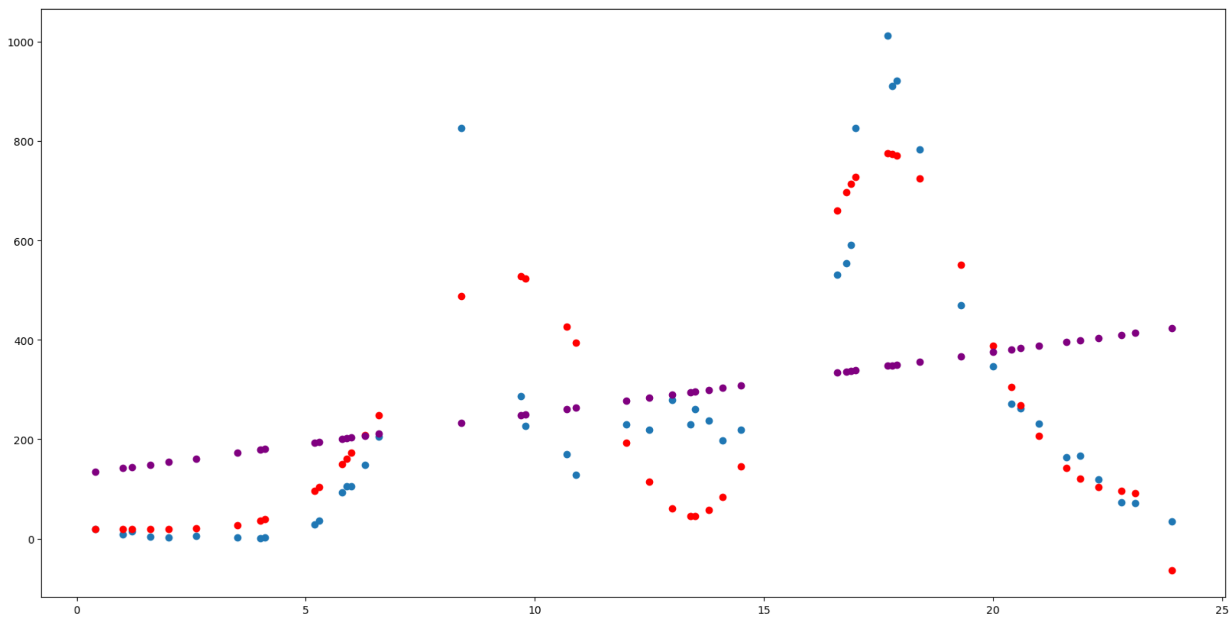
Out[132]: (695.9487707217071, 21.66694172833303, 0.6992783364740897)

In [133…
```
#Monday
xtrain2, xtest2, ytrain2, ytest2 = train_test_split(hour, mon, test_size = 0.2)
linear2 = linear_model.LinearRegression().fit(xtrain2, ytrain2)
```

In [134…
```
xtrain2_15 = PolynomialFeatures(degree = 15).fit_transform(xtrain2)
xtest2_15 = PolynomialFeatures(degree = 15).fit_transform(xtest2)

linear2_15 = linear_model.LinearRegression().fit(xtrain2_15, ytrain2)
```

In [135…
```
plt.scatter(xtest2, ytest2)
plt.scatter(xtest2, linear2_15.predict(xtest2_15), c = 'red')
plt.scatter(xtest2, linear2.predict(xtest2), c = 'purple')
```

Out[135]: <matplotlib.collections.PathCollection at 0x121a85cd990>



In [136…
```
(
metrics.mean_squared_error(ytest2, linear2_15.predict(xtest2_15)),
metrics.mean_absolute_error(ytest2, linear2_15.predict(xtest2_15)),
metrics.mean_absolute_percentage_error(ytest2, linear2_15.predict(xtest2_15))
)
```

Out[136]: (16726.443861718904, 95.70812407955282, 2.1637409995765275)

In [ ]: