

# Ben Roth Week 6 - Jupyter Notebook (Trees Regression)

March 6, 2020

- <https://scikit-learn.org/stable/modules/tree.html>
- <http://scikit-learn.org/stable/modules/generated/sklearn.tree.DecisionTreeRegressor.html>

```
In [1]: import sklearn
```

```
sklearn.__version__
```

```
Out[1]: '0.21.2'
```

```
In [2]: !pip3 install scikit-learn --upgrade
```

```
'pip3' is not recognized as an internal or external command,  
operable program or batch file.
```

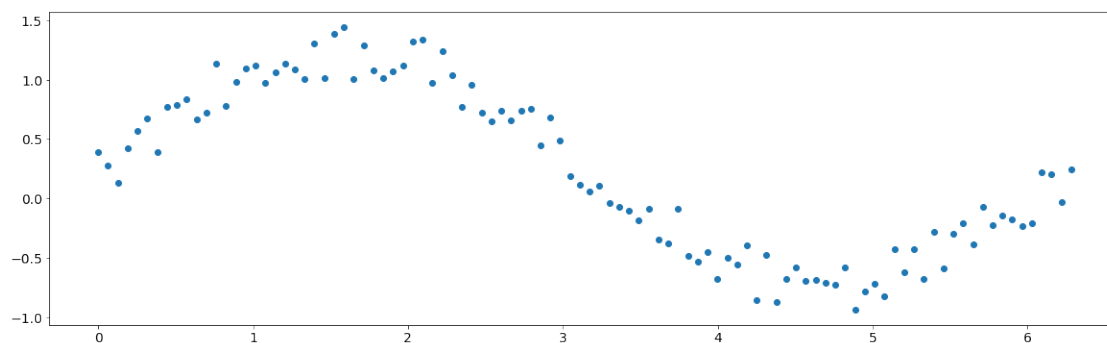
```
In [3]: import seaborn as sns  
import matplotlib.pyplot as plt  
%matplotlib inline  
import pandas as pd  
import numpy as np
```

```
In [4]: plt.rcParams['figure.figsize'] = (20, 6)  
plt.rcParams['font.size'] = 14
```

```
In [5]: x = np.linspace(0, 2* np.pi, 100)  
y = np.sin(x) + .5*np.random.random(100)
```

```
In [6]: plt.scatter(x, y)
```

```
Out[6]: <matplotlib.collections.PathCollection at 0x1fa0bec1c88>
```



```
In [7]: from sklearn import tree
```

```
In [8]: 2**16
```

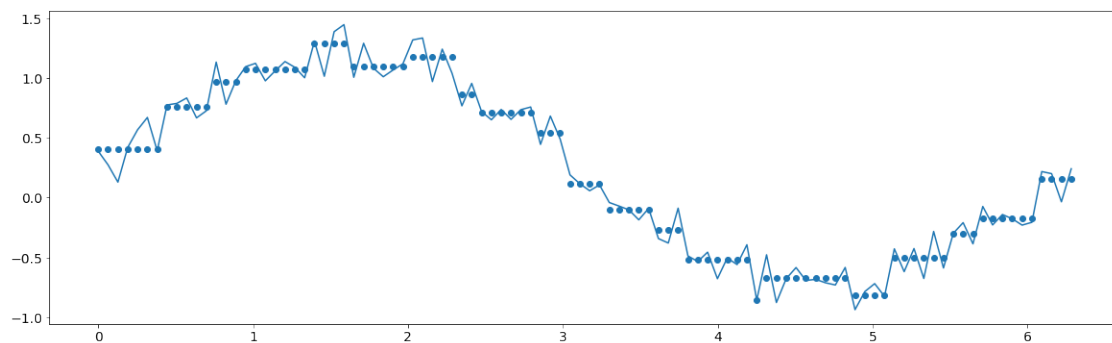
```
Out[8]: 65536
```

```
In [9]: regression = tree.DecisionTreeRegressor(max_depth=8, min_samples_split=8)
regression.fit(x.reshape(-1, 1), y)
```

```
yp = regression.predict(x.reshape(-1,1))
```

```
plt.scatter(x, yp)
plt.plot(x, y)
```

```
Out[9]: [<matplotlib.lines.Line2D at 0x1fa0dae73c8>]
```



```
In [10]: regression.predict([[2]])
```

```
Out[10]: array([1.17958191])
```

```
In [11]: path = regression.decision_path(x.reshape(-1, 1))
```

```
In [12]: path.todense()
```

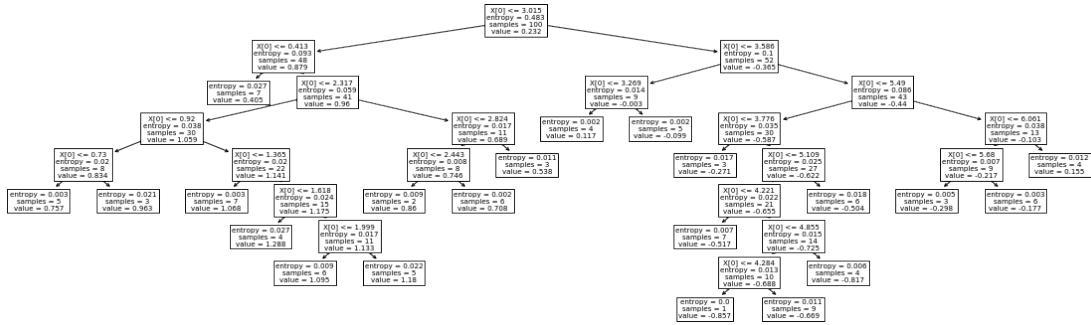
```
Out[12]: matrix([[1, 1, 1, ..., 0, 0, 0],
                 [1, 1, 1, ..., 0, 0, 0],
                 [1, 1, 1, ..., 0, 0, 0],
                 ...,
                 [1, 0, 0, ..., 0, 0, 1],
                 [1, 0, 0, ..., 0, 0, 1],
                 [1, 0, 0, ..., 0, 0, 1]], dtype=int64)
```

```
In [13]: tree.plot_tree(regression)
```

```

Out[13]: [Text(524.52, 308.04, 'X[0] <= 3.015\nentropy = 0.483\nsamples = 100\nvalue = 0.232'),
Text(290.16, 271.8, 'X[0] <= 0.413\nentropy = 0.093\nsamples = 48\nvalue = 0.879'),
Text(245.52, 235.56, 'entropy = 0.027\nsamples = 7\nvalue = 0.405'),
Text(334.8, 235.56, 'X[0] <= 2.317\nentropy = 0.059\nsamples = 41\nvalue = 0.96'),
Text(178.56, 199.32000000000002, 'X[0] <= 0.92\nentropy = 0.038\nsamples = 30\nvalue = 0.834'),
Text(89.28, 163.08, 'X[0] <= 0.73\nentropy = 0.02\nsamples = 8\nvalue = 0.834'),
Text(44.64, 126.84, 'entropy = 0.003\nsamples = 5\nvalue = 0.757'),
Text(133.92000000000002, 126.84, 'entropy = 0.021\nsamples = 3\nvalue = 0.963'),
Text(267.84000000000003, 163.08, 'X[0] <= 1.365\nentropy = 0.02\nsamples = 22\nvalue = 1.068'),
Text(223.2, 126.84, 'entropy = 0.003\nsamples = 7\nvalue = 1.068'),
Text(312.48, 126.84, 'X[0] <= 1.618\nentropy = 0.024\nsamples = 15\nvalue = 1.175'),
Text(267.84000000000003, 90.60000000000002, 'entropy = 0.027\nsamples = 4\nvalue = 1.175'),
Text(357.12, 90.60000000000002, 'X[0] <= 1.999\nentropy = 0.017\nsamples = 11\nvalue = 1.095'),
Text(312.48, 54.360000000000014, 'entropy = 0.009\nsamples = 6\nvalue = 1.095'),
Text(401.76, 54.360000000000014, 'entropy = 0.022\nsamples = 5\nvalue = 1.18'),
Text(491.04, 199.32000000000002, 'X[0] <= 2.824\nentropy = 0.017\nsamples = 11\nvalue = 1.18'),
Text(446.4, 163.08, 'X[0] <= 2.443\nentropy = 0.008\nsamples = 8\nvalue = 0.746'),
Text(401.76, 126.84, 'entropy = 0.009\nsamples = 2\nvalue = 0.86'),
Text(491.04, 126.84, 'entropy = 0.002\nsamples = 6\nvalue = 0.708'),
Text(535.68000000000001, 163.08, 'entropy = 0.011\nsamples = 3\nvalue = 0.538'),
Text(758.88, 271.8, 'X[0] <= 3.586\nentropy = 0.1\nsamples = 52\nvalue = -0.365'),
Text(624.96, 235.56, 'X[0] <= 3.269\nentropy = 0.014\nsamples = 9\nvalue = -0.003'),
Text(580.32, 199.32000000000002, 'entropy = 0.002\nsamples = 4\nvalue = 0.117'),
Text(669.6, 199.32000000000002, 'entropy = 0.002\nsamples = 5\nvalue = -0.099'),
Text(892.8, 235.56, 'X[0] <= 5.49\nentropy = 0.086\nsamples = 43\nvalue = -0.44'),
Text(758.88, 199.32000000000002, 'X[0] <= 3.776\nentropy = 0.035\nsamples = 30\nvalue = -0.271'),
Text(714.24, 163.08, 'entropy = 0.017\nsamples = 3\nvalue = -0.271'),
Text(803.52, 163.08, 'X[0] <= 5.109\nentropy = 0.025\nsamples = 27\nvalue = -0.622'),
Text(758.88, 126.84, 'X[0] <= 4.221\nentropy = 0.022\nsamples = 21\nvalue = -0.655'),
Text(714.24, 90.60000000000002, 'entropy = 0.007\nsamples = 7\nvalue = -0.517'),
Text(803.52, 90.60000000000002, 'X[0] <= 4.855\nentropy = 0.015\nsamples = 14\nvalue = -0.517'),
Text(758.88, 54.360000000000014, 'X[0] <= 4.284\nentropy = 0.013\nsamples = 10\nvalue = -0.817'),
Text(714.24, 18.120000000000005, 'entropy = 0.0\nsamples = 1\nvalue = -0.857'),
Text(803.52, 18.120000000000005, 'entropy = 0.011\nsamples = 9\nvalue = -0.669'),
Text(848.16, 54.360000000000014, 'entropy = 0.006\nsamples = 4\nvalue = -0.817'),
Text(848.16, 126.84, 'entropy = 0.018\nsamples = 6\nvalue = -0.504'),
Text(1026.72, 199.32000000000002, 'X[0] <= 6.061\nentropy = 0.038\nsamples = 13\nvalue = -0.217'),
Text(982.08, 163.08, 'X[0] <= 5.68\nentropy = 0.007\nsamples = 9\nvalue = -0.217'),
Text(937.44, 126.84, 'entropy = 0.005\nsamples = 3\nvalue = -0.298'),
Text(1026.72, 126.84, 'entropy = 0.003\nsamples = 6\nvalue = -0.177'),
Text(1071.36000000000001, 163.08, 'entropy = 0.012\nsamples = 4\nvalue = 0.155')]

```



In [14]: bikeshare = pd.read\_csv('../data/bikeshare\_daily\_agg.csv', index\_col='hour\_of\_day')

In [15]: bikeshare

Out[15]:

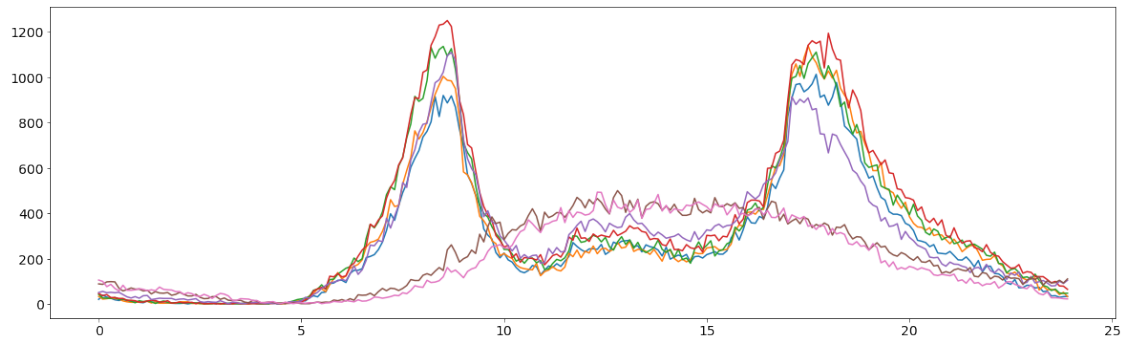
	0	1	2	3	4	5	6
hour_of_day							
0.0	21.0	34.0	43.0	47.0	51.0	89.0	106.0
0.1	39.0	22.0	27.0	37.0	56.0	87.0	100.0
0.2	31.0	24.0	26.0	42.0	50.0	98.0	77.0
0.3	26.0	27.0	25.0	29.0	52.0	99.0	87.0
0.4	19.0	24.0	29.0	29.0	50.0	98.0	69.0
0.5	16.0	23.0	20.0	25.0	52.0	70.0	58.0
0.6	21.0	14.0	22.0	25.0	42.0	58.0	83.0
0.7	16.0	10.0	17.0	17.0	32.0	64.0	61.0
0.8	11.0	8.0	13.0	17.0	27.0	71.0	61.0
0.9	11.0	8.0	6.0	15.0	33.0	66.0	63.0
1.0	8.0	9.0	15.0	9.0	26.0	66.0	68.0
1.1	6.0	11.0	11.0	9.0	37.0	58.0	65.0
1.2	14.0	12.0	13.0	14.0	38.0	61.0	59.0
1.3	8.0	5.0	10.0	17.0	20.0	45.0	63.0
1.4	10.0	10.0	3.0	16.0	23.0	55.0	59.0
1.5	6.0	4.0	9.0	9.0	26.0	49.0	75.0
1.6	4.0	4.0	14.0	10.0	25.0	48.0	65.0
1.7	5.0	5.0	8.0	15.0	25.0	51.0	63.0
1.8	4.0	4.0	5.0	4.0	25.0	39.0	62.0
1.9	3.0	4.0	6.0	6.0	19.0	43.0	55.0
2.0	3.0	10.0	5.0	9.0	22.0	52.0	55.0
2.1	4.0	10.0	6.0	5.0	23.0	43.0	43.0
2.2	1.0	10.0	5.0	7.0	18.0	36.0	50.0
2.3	4.0	3.0	5.0	8.0	21.0	36.0	46.0
2.4	4.0	3.0	5.0	2.0	24.0	43.0	36.0
2.5	5.0	2.0	3.0	7.0	11.0	30.0	34.0
2.6	6.0	2.0	2.0	1.0	8.0	24.0	43.0
2.7	3.0	2.0	2.0	2.0	11.0	25.0	36.0
2.8	5.0	2.0	2.0	3.0	9.0	33.0	25.0

2.9	2.0	NaN	4.0	1.0	8.0	33.0	38.0
...	...	...	...	...	...	...	...
21.0	232.0	266.0	300.0	292.0	185.0	137.0	125.0
21.1	214.0	286.0	266.0	336.0	176.0	151.0	132.0
21.2	195.0	263.0	271.0	293.0	175.0	156.0	102.0
21.3	194.0	231.0	282.0	268.0	167.0	150.0	107.0
21.4	208.0	246.0	252.0	277.0	162.0	146.0	92.0
21.5	189.0	257.0	262.0	279.0	139.0	161.0	114.0
21.6	164.0	260.0	264.0	249.0	158.0	123.0	92.0
21.7	192.0	229.0	253.0	244.0	162.0	120.0	95.0
21.8	142.0	193.0	242.0	231.0	148.0	139.0	81.0
21.9	167.0	197.0	215.0	262.0	175.0	135.0	89.0
22.0	167.0	198.0	211.0	228.0	147.0	111.0	88.0
22.1	135.0	214.0	229.0	215.0	138.0	123.0	99.0
22.2	133.0	180.0	179.0	211.0	155.0	120.0	71.0
22.3	120.0	169.0	177.0	187.0	141.0	106.0	82.0
22.4	94.0	137.0	138.0	172.0	109.0	123.0	98.0
22.5	87.0	132.0	152.0	158.0	137.0	114.0	99.0
22.6	109.0	141.0	157.0	160.0	127.0	115.0	87.0
22.7	72.0	123.0	140.0	174.0	141.0	112.0	81.0
22.8	73.0	114.0	117.0	136.0	92.0	86.0	72.0
22.9	83.0	106.0	120.0	143.0	96.0	105.0	68.0
23.0	82.0	111.0	111.0	140.0	122.0	117.0	86.0
23.1	71.0	115.0	132.0	122.0	93.0	108.0	61.0
23.2	74.0	62.0	105.0	121.0	99.0	121.0	46.0
23.3	55.0	80.0	82.0	121.0	104.0	84.0	41.0
23.4	57.0	63.0	76.0	108.0	93.0	103.0	54.0
23.5	36.0	65.0	60.0	94.0	80.0	93.0	28.0
23.6	37.0	61.0	66.0	100.0	81.0	95.0	28.0
23.7	30.0	42.0	49.0	80.0	101.0	105.0	27.0
23.8	33.0	52.0	47.0	79.0	91.0	93.0	24.0
23.9	34.0	33.0	48.0	65.0	105.0	111.0	23.0

[240 rows x 7 columns]

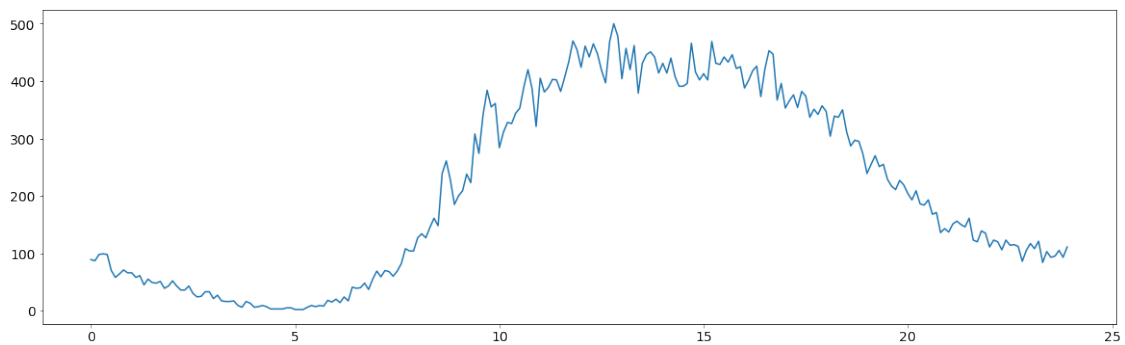
In [16]: plt.plot(bikeshare)

Out[16]: [<matplotlib.lines.Line2D at 0x1fa0dfcd860>,  
 <matplotlib.lines.Line2D at 0x1fa0dfcd9b0>,  
 <matplotlib.lines.Line2D at 0x1fa0dfcdb00>,  
 <matplotlib.lines.Line2D at 0x1fa0dfcdc50>,  
 <matplotlib.lines.Line2D at 0x1fa0dfcdda0>,  
 <matplotlib.lines.Line2D at 0x1fa0dfcdef0>,  
 <matplotlib.lines.Line2D at 0x1fa0dfd9080>]



```
In [17]: plt.plot(bikeshare['5'])
```

```
Out[17]: [<matplotlib.lines.Line2D at 0x1fa0dbc76d8>]
```



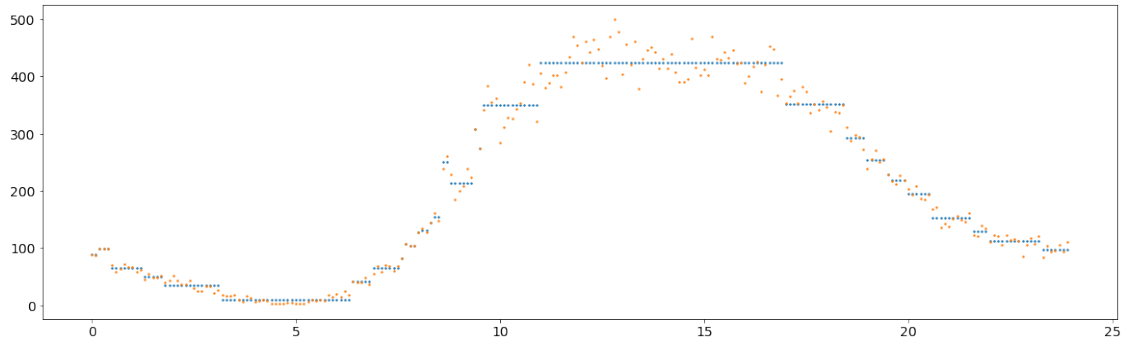
```
In [18]: hours = bikeshare.index.values.reshape(-1,1)
```

```
bike_reg = tree.DecisionTreeRegressor(max_depth=5)
bike_reg.fit(hours, bikeshare['5'].fillna(0))
```

```
bike_pred = bike_reg.predict(hours)
```

```
plt.scatter(hours, bike_pred, s=2)
plt.scatter(hours, bikeshare['5'], s=2)
```

```
Out[18]: <matplotlib.collections.PathCollection at 0x1fa0e055630>
```



- 1 Use the bikeshare dataset (see above) and choose a weekday (0,1,2,3,4).
- 2 1. Create 5 Decision Tree Regressors using `max_depth=4,5,6,7,8`. For each one of these models, calculate the MSE between the predicted values from the model (`bike_pred`) and the actual values (`bikeshare['n']`). Create a plot showing the predictions along with the actuals. You may also show the `print_tree()` for a sanity check as well.

```
In [19]: bikeshare['2'].index
```

```
Out[19]: Float64Index([ 0.0,  0.1,  0.2,  0.3,  0.4,  0.5,  0.6,  0.7,  0.8,  0.9,
...
                23.0, 23.1, 23.2, 23.3, 23.4, 23.5, 23.6, 23.7, 23.8, 23.9],
                dtype='float64', name='hour_of_day', length=240)
```

```
In [27]: from sklearn.metrics import mean_squared_error
```

```
max_depth = [4, 5, 6, 7, 8]
```

```
wed = bikeshare['2']
```

```
wed = wed.fillna(0)
```

```
mse = []
```

```
preds = []
```

```
for depth in max_depth:
```

```
    dt = tree.DecisionTreeRegressor(max_depth=depth)
```

```
    dt.fit(np.array(wed.index).reshape(-1, 1), wed.values)
```

```
    pred = dt.predict(np.array(wed.index).reshape(-1, 1))
```

```
    preds.append(pred)
```

```
mse.append(mean_squared_error(y_true = wed.values, y_pred = pred))
```

```
for i in range(len(mse)):
    print('Max Depth:', max_depth[i], ', MSE: ', mse[i])
```

Max Depth: 4 , MSE: 12346.81080131674  
Max Depth: 5 , MSE: 6101.514951765633  
Max Depth: 6 , MSE: 1669.1621186591121  
Max Depth: 7 , MSE: 596.2443307249763  
Max Depth: 8 , MSE: 300.7029178072744

In [29]: preds

[illegible]





[illegible]

3.74193548,	3.74193548,	3.74193548,	3.74193548,
3.74193548,	3.74193548,	3.74193548,	3.74193548,
3.74193548,	23.	, 23.	, 23.
34.	, 61.	, 66.	, 85.
66.	, 108.	, 110.	, 132.
145.	, 158.	, 164.	, 203.
187.	, 200.	, 290.	, 350.
350.	, 350.	, 406.	, 482.
510.5	, 510.5	, 608.	, 647.
763.	, 763.	, 904.66666667,	904.66666667,
904.66666667,	1088.125	, 1088.125	, 1088.125
1088.125	, 1088.125	, 1088.125	, 1088.125
1088.125	, 903.	, 709.	, 667.
640.	, 521.	, 406.	, 406.
406.	, 341.	, 270.25	, 270.25
270.25	, 270.25	, 189.07142857,	189.07142857,
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255.02439024,	335.33333333,	335.33333333,	335.33333333,
423.2	, 423.2	, 423.2	, 423.2
423.2	, 594.	, 594.	, 594.
594.	, 980.4375	, 980.4375	, 980.4375
980.4375	, 980.4375	, 980.4375	, 980.4375
980.4375	, 980.4375	, 980.4375	, 980.4375
980.4375	, 980.4375	, 980.4375	, 980.4375
980.4375	, 641.09090909,	641.09090909,	641.09090909,
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641.09090909,	641.09090909,	641.09090909,	641.09090909,
423.125	, 423.125	, 423.125	, 423.125
423.125	, 423.125	, 423.125	, 423.125
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177.55555556,	177.55555556,	177.55555556,	177.55555556,
177.55555556,	177.55555556,	177.55555556,	177.55555556,
84.41666667,	84.41666667,	84.41666667,	84.41666667,

[illegible]

```

999.33333333, 767.75 , 767.75 , 767.75 ,
767.75 , 568.71428571, 568.71428571, 568.71428571,
568.71428571, 568.71428571, 568.71428571, 568.71428571,
438. , 438. , 438. , 438. ,
438. , 438. , 378.5 , 378.5 ,
307. , 307. , 307. , 307. ,
307. , 307. , 307. , 261.5 ,
261.5 , 261.5 , 261.5 , 261.5 ,
261.5 , 261.5 , 261.5 , 218.33333333,
218.33333333, 218.33333333, 157.16666667, 157.16666667,
157.16666667, 157.16666667, 157.16666667, 157.16666667,
117. , 117. , 117. , 117. ,
117. , 61.14285714, 61.14285714, 61.14285714,
61.14285714, 61.14285714, 61.14285714, 61.14285714]),
array([ 43. , 27. , 25.5 , 25.5 ,
29. , 20. , 22. , 17. ,
9.5 , 9.5 , 13. , 13. ,
13. , 6.5 , 6.5 , 10.33333333,
10.33333333, 10.33333333, 5.28571429, 5.28571429,
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2.54545455, 2.54545455, 2.54545455, 2.54545455,
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2.54545455, 2.54545455, 2.54545455, 2.54545455,
2.54545455, 2.54545455, 2.54545455, 9. ,
14. , 20. , 23. , 26. ,
34. , 61. , 66. , 85. ,
66. , 108. , 110. , 132. ,
145. , 158. , 164. , 203. ,
187. , 200. , 290. , 351. ,
336. , 363. , 406. , 482. ,
517. , 504. , 608. , 647. ,
733. , 793. , 915. , 893. ,
906. , 984. , 1114.33333333, 1114.33333333,
1114.33333333, 1114.33333333, 1114.33333333, 1114.33333333,
1035. , 903. , 709. , 667. ,
640. , 521. , 436. , 399. ,
383. , 341. , 311. , 289. ,
241. , 240. , 221. , 194.6 ,
194.6 , 194.6 , 194.6 , 194.6 ,
181.625 , 181.625 , 181.625 , 181.625 ,
181.625 , 181.625 , 181.625 , 181.625 ,
235. , 278.23529412, 278.23529412, 278.23529412,
278.23529412, 278.23529412, 278.23529412, 278.23529412,
278.23529412, 278.23529412, 278.23529412, 278.23529412,
278.23529412, 278.23529412, 278.23529412, 278.23529412,
278.23529412, 278.23529412, 228.46153846, 228.46153846,

```

```

228.46153846, 228.46153846, 228.46153846, 228.46153846,
228.46153846, 228.46153846, 228.46153846, 228.46153846,
228.46153846, 228.46153846, 228.46153846, 252.1,
252.1, 252.1, 252.1, 252.1,
252.1, 252.1, 252.1, 252.1,
252.1, 339., 322., 345.,
414., 421., 445., 418.,
418., 525., 604.5, 604.5,
642., 697., 1017.69230769, 1017.69230769,
1017.69230769, 1017.69230769, 1017.69230769, 1017.69230769,
1017.69230769, 1017.69230769, 1017.69230769, 1017.69230769,
1017.69230769, 1017.69230769, 1017.69230769, 880.,
880., 779., 779., 779.,
734., 611.25, 611.25, 611.25,
611.25, 512., 512., 512.,
456.33333333, 456.33333333, 456.33333333, 419.66666667,
419.66666667, 419.66666667, 388., 369.,
318.25, 318.25, 318.25, 318.25,
292., 292., 292., 273.,
273., 273., 254.6, 254.6,
254.6, 254.6, 254.6, 213.,
213., 229., 178., 178.,
146.75, 146.75, 146.75, 146.75,
120., 120., 120., 120.,
105., 71., 71., 71.,
71., 48., 48., 48., 48. ]])

```

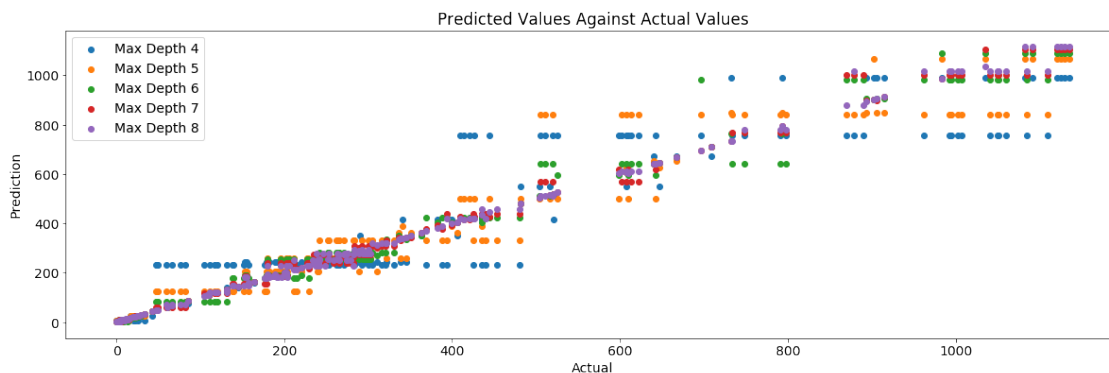
```
In [35]: colours = ['r', 'g', 'm', 'black', 'blue']
```

```

for i in range(len(preds)):
    plt.scatter(wed.values, preds[i], label = ('Max Depth ' + str(max_depth[i])))

plt.title('Predicted Values Against Actual Values')
plt.xlabel('Actual')
plt.ylabel('Prediction')
plt.legend(loc="upper left")
plt.show()

```



```
In [30]: 'max depth' + str(1)
```

```
Out[30]: 'max depth1'
```

**3 2. Using the 5 models created with various max\_depth values, calculate the MSE between the predicted values (bike\_pred) and values from all of the weekdays [0,1,2,3,4]. You should have 25 total MSE values, 5 values for each max\_depth.**

```
In [38]: weekday = ['0', '1', '2', '3', '4']
```

```
bikeshare = bikeshare.fillna(0)
```

```
for day in weekday:
    for i in range(len(preds)):
        mse = mean_squared_error(y_true = bikeshare[day].values, y_pred = preds[i])
        print('Max Depth:', max_depth[i], ', MSE: ', mse, ', Weekday: ', day)
```

```
Max Depth: 4 , MSE: 16200.667148719334 , Weekday: 0
Max Depth: 5 , MSE: 10579.826219781049 , Weekday: 0
Max Depth: 6 , MSE: 7088.172542190728 , Weekday: 0
Max Depth: 7 , MSE: 5955.647449694338 , Weekday: 0
Max Depth: 8 , MSE: 5792.606878882963 , Weekday: 0
Max Depth: 4 , MSE: 15114.876464195526 , Weekday: 1
Max Depth: 5 , MSE: 8084.399600813383 , Weekday: 1
Max Depth: 6 , MSE: 4200.2675531109235 , Weekday: 1
Max Depth: 7 , MSE: 3006.770403405211 , Weekday: 1
Max Depth: 8 , MSE: 2847.6663810025757 , Weekday: 1
Max Depth: 4 , MSE: 12346.81080131674 , Weekday: 2
Max Depth: 5 , MSE: 6101.514951765633 , Weekday: 2
Max Depth: 6 , MSE: 1669.1621186591121 , Weekday: 2
Max Depth: 7 , MSE: 596.2443307249763 , Weekday: 2
Max Depth: 8 , MSE: 300.7029178072744 , Weekday: 2
Max Depth: 4 , MSE: 16400.019857954547 , Weekday: 3
Max Depth: 5 , MSE: 8476.439264264578 , Weekday: 3
Max Depth: 6 , MSE: 4047.2954779416596 , Weekday: 3
Max Depth: 7 , MSE: 2648.647442047062 , Weekday: 3
Max Depth: 8 , MSE: 2474.806256531459 , Weekday: 3
Max Depth: 4 , MSE: 13739.871225198413 , Weekday: 4
Max Depth: 5 , MSE: 12681.66137906294 , Weekday: 4
Max Depth: 6 , MSE: 9487.773181941471 , Weekday: 4
Max Depth: 7 , MSE: 9019.185179517614 , Weekday: 4
Max Depth: 8 , MSE: 8853.029768277067 , Weekday: 4
```

**4 3. (2 cont'd) Describe which max\_depth you would recommend based on the groups of MSE values. Use the idea of generality of the model for your argument along with the MSE values as proof.**

Looking at the above printed statement, I would argue that a max depth of at least 8 should be used for the model. In each of the above 25 models, a max depth of 8 has by far the lowest MSE for each weekday when compared to lower max depth values. Although the MSE values are better for a max depth of 8, I would hesitate to use a model trained on one day for a different; the only weekday values that produce a relatively low MSE with increased depth