Trees Regression HW 6

March 10, 2020

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

[1]:
```python
import sklearn

sklearn.__version__
```

[1]: '0.22.1'

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

```
Collecting scikit-learn
  Downloading https://files.pythonhosted.org/packages/64/57/23176044d9371e
1af286176fd61cf7f74ed46d0b99122624ab93b3f32715/scikit_learn-0.22.2.post1-cp37-cp
37m-macosx_10_9_x86_64.whl (7.1MB)
    100% |                 | 7.1MB 7.3MB/s eta 0:00:01
Collecting numpy>=1.11.0 (from scikit-learn)
  Using cached https://files.pythonhosted.org/packages/2f/5b/2cc2b9285e8b2ca8d2c
1e4a2cbf1b12d70a2488ea78170de1909bca725f2/numpy-1.18.1-cp37-cp37m-macosx_10_9_x8
6_64.whl
Collecting scipy>=0.17.0 (from scikit-learn)
  Using cached https://files.pythonhosted.org/packages/85/7a/ae480be23b768910a93
27c33517ced4623ba88dc035f9ce0206657c353a9/scipy-1.4.1-cp37-cp37m-macosx_10_6_int
el.whl
Collecting joblib>=0.11 (from scikit-learn)
  Downloading https://files.pythonhosted.org/packages/28/5c/cf6a2b65a321c4
a209efcdf64c2689efae2cb62661f8f6f4bb28547cf1bf/joblib-0.14.1-py2.py3-none-
any.whl (294kB)
    100% |                 | 296kB 28.6MB/s ta 0:00:01
Installing collected packages: numpy, scipy, joblib, scikit-learn
Could not install packages due to an EnvironmentError: [Errno 13]
Permission denied:
'/Library/Frameworks/Python.framework/Versions/3.7/lib/python3.7/site-
packages/numpy'
Consider using the `--user` option or check the permissions.
```

```
You are using pip version 10.0.1, however version 20.0.2 is available.
You should consider upgrading via the 'pip install --upgrade pip' command.
```

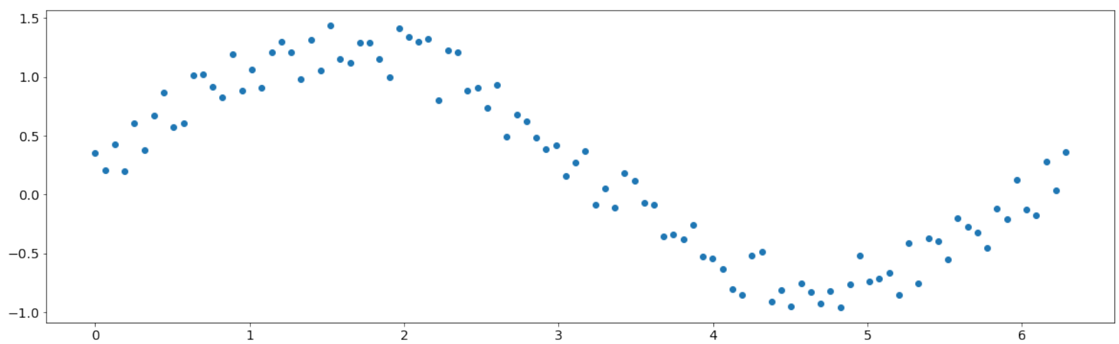
[3]:
```
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import pandas as pd
import numpy as np
```

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

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

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

[6]:
```
<matplotlib.collections.PathCollection at 0x1a184c8cc0>
```



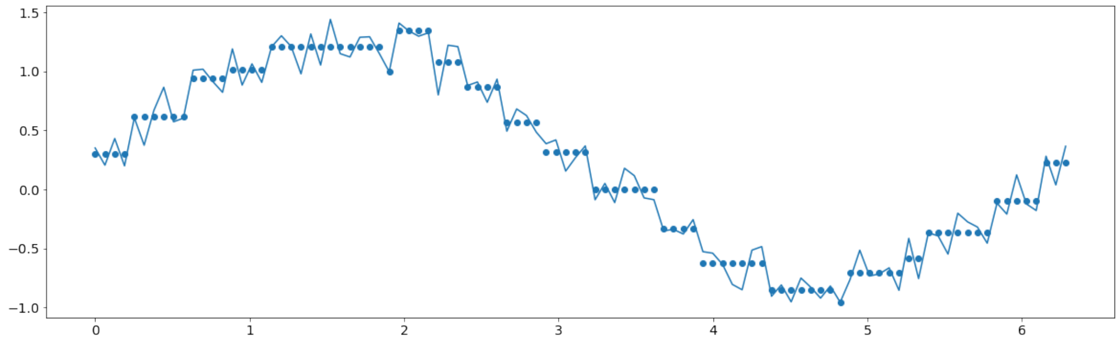
[7]:
```
from sklearn import tree
```

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

[8]:
```
65536
```

[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)
```

[9]:
```
[<matplotlib.lines.Line2D at 0x1a1918f7b8>]
```



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

[10]:
```
array([1.34292252])
```

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

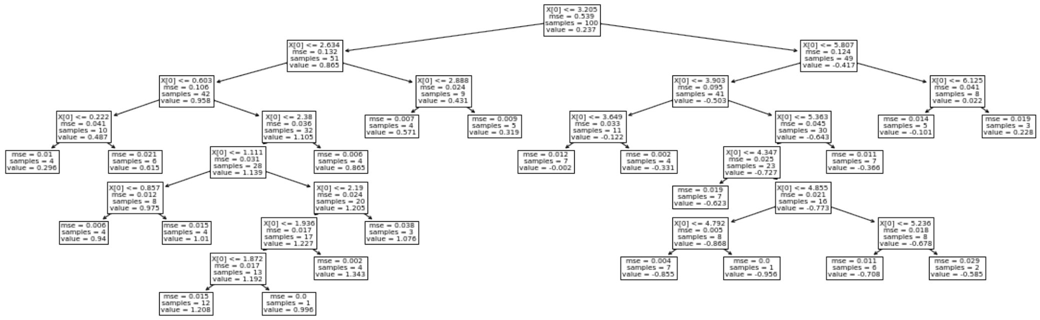
[12]:
```
path.todense()
```

[12]:
```
matrix([[1, 1, 1, …, 0, 0, 0],
        [1, 1, 1, …, 0, 0, 0],
        [1, 1, 1, …, 0, 0, 0],
        …,
        [1, 0, 0, …, 1, 0, 1],
        [1, 0, 0, …, 1, 0, 1],
        [1, 0, 0, …, 1, 0, 1]])
```

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

[13]:
```
[Text(614.976,314.651,'X[0] <= 3.205\nmse = 0.539\nsamples = 100\nvalue =
0.237'),
 Text(347.595,277.633,'X[0] <= 2.634\nmse = 0.132\nsamples = 51\nvalue =
0.865'),
 Text(213.905,240.616,'X[0] <= 0.603\nmse = 0.106\nsamples = 42\nvalue =
0.958'),
 Text(106.952,203.598,'X[0] <= 0.222\nmse = 0.041\nsamples = 10\nvalue =
0.487'),
 Text(53.4762,166.58,'mse = 0.01\nsamples = 4\nvalue = 0.296'),
 Text(160.429,166.58,'mse = 0.021\nsamples = 6\nvalue = 0.615'),
 Text(320.857,203.598,'X[0] <= 2.38\nmse = 0.036\nsamples = 32\nvalue = 1.105'),
 Text(267.381,166.58,'X[0] <= 1.111\nmse = 0.031\nsamples = 28\nvalue = 1.139'),
 Text(160.429,129.562,'X[0] <= 0.857\nmse = 0.012\nsamples = 8\nvalue = 0.975'),
 Text(106.952,92.5444,'mse = 0.006\nsamples = 4\nvalue = 0.94'),
 Text(213.905,92.5444,'mse = 0.015\nsamples = 4\nvalue = 1.01'),
 Text(374.333,129.562,'X[0] <= 2.19\nmse = 0.024\nsamples = 20\nvalue = 1.205'),
```

```
 Text(320.857,92.5444,'X[0] <= 1.936\nmse = 0.017\nsamples = 17\nvalue =
1.227'),
 Text(267.381,55.5267,'X[0] <= 1.872\nmse = 0.017\nsamples = 13\nvalue =
1.192'),
 Text(213.905,18.5089,'mse = 0.015\nsamples = 12\nvalue = 1.208'),
 Text(320.857,18.5089,'mse = 0.0\nsamples = 1\nvalue = 0.996'),
 Text(374.333,55.5267,'mse = 0.002\nsamples = 4\nvalue = 1.343'),
 Text(427.81,92.5444,'mse = 0.038\nsamples = 3\nvalue = 1.076'),
 Text(374.333,166.58,'mse = 0.006\nsamples = 4\nvalue = 0.865'),
 Text(481.286,240.616,'X[0] <= 2.888\nmse = 0.024\nsamples = 9\nvalue = 0.431'),
 Text(427.81,203.598,'mse = 0.007\nsamples = 4\nvalue = 0.571'),
 Text(534.762,203.598,'mse = 0.009\nsamples = 5\nvalue = 0.319'),
 Text(882.357,277.633,'X[0] <= 5.807\nmse = 0.124\nsamples = 49\nvalue =
-0.417'),
 Text(748.667,240.616,'X[0] <= 3.903\nmse = 0.095\nsamples = 41\nvalue =
-0.503'),
 Text(641.714,203.598,'X[0] <= 3.649\nmse = 0.033\nsamples = 11\nvalue =
-0.122'),
 Text(588.238,166.58,'mse = 0.012\nsamples = 7\nvalue = -0.002'),
 Text(695.19,166.58,'mse = 0.002\nsamples = 4\nvalue = -0.331'),
 Text(855.619,203.598,'X[0] <= 5.363\nmse = 0.045\nsamples = 30\nvalue =
-0.643'),
 Text(802.143,166.58,'X[0] <= 4.347\nmse = 0.025\nsamples = 23\nvalue =
-0.727'),
 Text(748.667,129.562,'mse = 0.019\nsamples = 7\nvalue = -0.623'),
 Text(855.619,129.562,'X[0] <= 4.855\nmse = 0.021\nsamples = 16\nvalue =
-0.773'),
 Text(748.667,92.5444,'X[0] <= 4.792\nmse = 0.005\nsamples = 8\nvalue =
-0.868'),
 Text(695.19,55.5267,'mse = 0.004\nsamples = 7\nvalue = -0.855'),
 Text(802.143,55.5267,'mse = 0.0\nsamples = 1\nvalue = -0.956'),
 Text(962.571,92.5444,'X[0] <= 5.236\nmse = 0.018\nsamples = 8\nvalue =
-0.678'),
 Text(909.095,55.5267,'mse = 0.011\nsamples = 6\nvalue = -0.708'),
 Text(1016.05,55.5267,'mse = 0.029\nsamples = 2\nvalue = -0.585'),
 Text(909.095,166.58,'mse = 0.011\nsamples = 7\nvalue = -0.366'),
 Text(1016.05,240.616,'X[0] <= 6.125\nmse = 0.041\nsamples = 8\nvalue = 0.022'),
 Text(962.571,203.598,'mse = 0.014\nsamples = 5\nvalue = -0.101'),
 Text(1069.52,203.598,'mse = 0.019\nsamples = 3\nvalue = 0.228')]
```



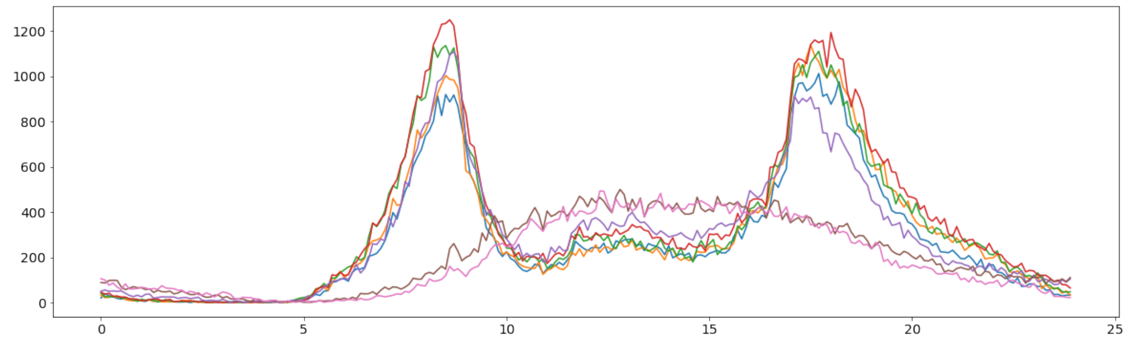
[14]:
```
bikeshare = pd.read_csv('../data/bikeshare_daily_agg.csv',␣
↪index_col='hour_of_day')
```

[15]:
```
bikeshare
```

[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
…             …     …     …      …      …      …      …
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]
```

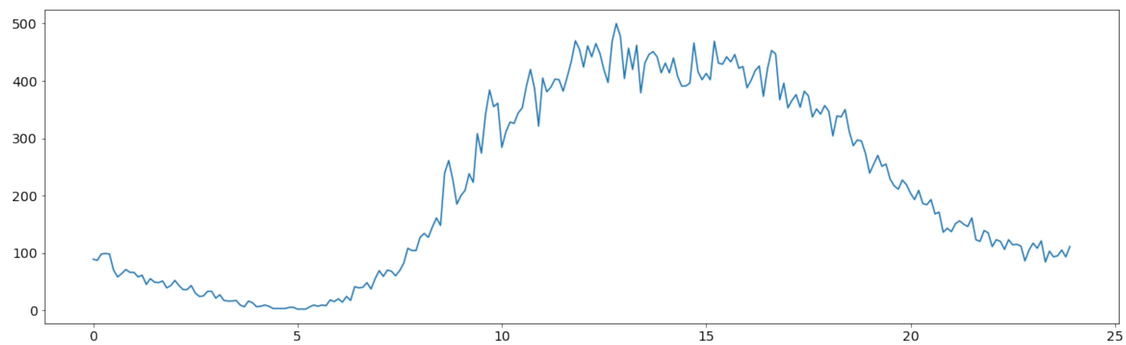
[16]:
```
plt.plot(bikeshare)
```

[16]:
```
[<matplotlib.lines.Line2D at 0x103b2b550>,
 <matplotlib.lines.Line2D at 0x103b2b748>,
 <matplotlib.lines.Line2D at 0x103b2b898>,
 <matplotlib.lines.Line2D at 0x103b2b9e8>,
 <matplotlib.lines.Line2D at 0x103b2bb38>,
 <matplotlib.lines.Line2D at 0x103b2bc88>,
 <matplotlib.lines.Line2D at 0x103b2bdd8>]
```



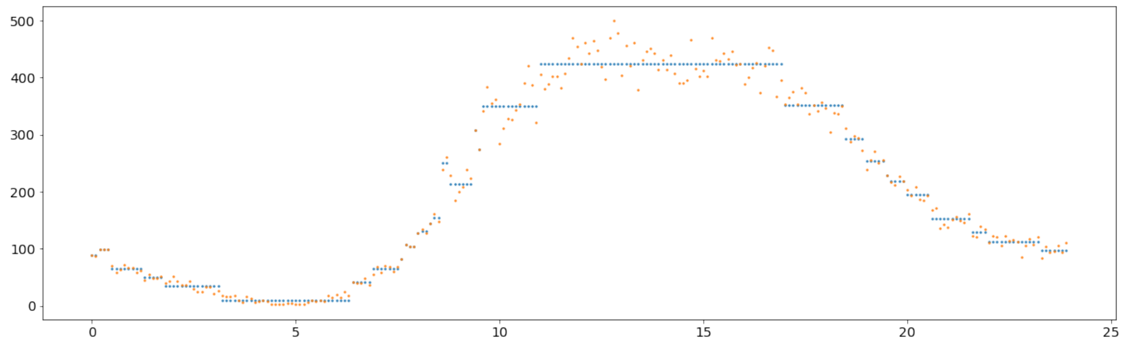
[17]:
```
plt.plot(bikeshare['5'])
```

[17]: [<matplotlib.lines.Line2D at 0x1a19a45860>]



[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)
```

[18]: <matplotlib.collections.PathCollection at 0x1a19c76198>



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.

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`.

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.

[167]:

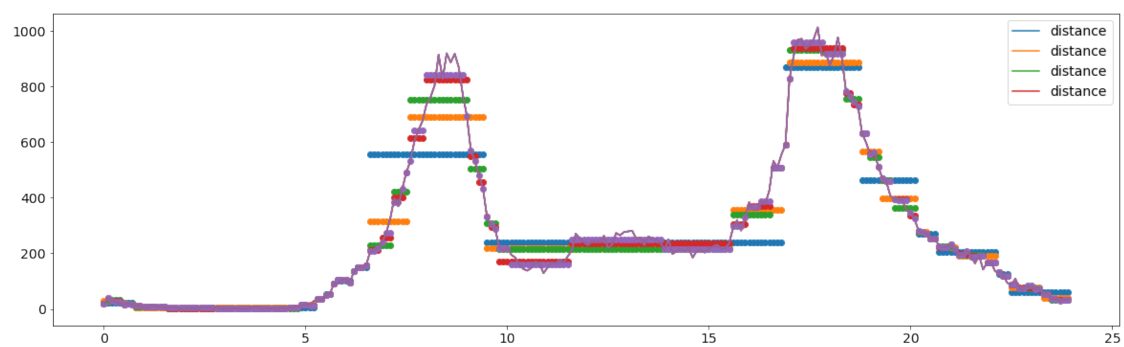
```
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import train_test_split

# extract subset of bikeshare data for monday and organize the dataframe.
monday_data = bikeshare.loc[:,'0'].reset_index().fillna(0)
print(monday_data.shape)
monday_data.columns = ['hour','distance']

# peace of mind that theres no NaN values in the data set.
```

```
print('Total NaN vals: ' + str(monday_data.distance.isna().sum())) # verify the␣
↪correction worked.


# test and train data.
x_train, x_test, y_train, y_test = train_test_split(monday_data.hour,␣
↪monday_data.distance, train_size = .8)


# iterate through 4:8 for max depth.
for i in range(4,9):

    # create model to answer Q1.
    regression = tree.DecisionTreeRegressor(max_depth=i)
    regression.fit(np.array(x_train).reshape(-1,1) , y_train)
    # predict values on model.
    pred_vals = regression.predict(np.array(monday_data.hour).reshape(-1,1))

    # plot graphs onto the original data.
    plt.scatter(monday_data.hour, pred_vals)
    plt.legend()
    plt.plot(monday_data.hour, monday_data.distance)
    mse = mean_squared_error(monday_data.distance, pred_vals)
    print('For max_depth = ' + str(i) + ": MSE = " + str(mse))

    for j in range(0,5):
        day_of_week = bikeshare.iloc[:,j].reset_index().fillna(0)
        #print(day_of_week)
        #print(day_of_week.iloc[:,1])
        mse_per_day = mean_squared_error(bikeshare.iloc[:,j].fillna(0),␣
↪pred_vals)

        print(f'For day = {j}  MSE = {mse_per_day:0.2f}  and max_depth = {i}␣
↪RMSE = {np.sqrt(mse_per_day):0.2f}')
    # run model against the other days of the week in the data set.
```

```
No handles with labels found to put in legend.
```

```
(240, 2)
Total NaN vals: 0
For max_depth = 4: MSE = 10376.405722311105
For day = 0  MSE = 10376.41  and max_depth = 4 RMSE = 101.86
For day = 1  MSE = 14325.53  and max_depth = 4 RMSE = 119.69
For day = 2  MSE = 19741.58  and max_depth = 4 RMSE = 140.50
For day = 3  MSE = 28348.12  and max_depth = 4 RMSE = 168.37
```

```
For day = 4  MSE = 18790.31  and max_depth = 4 RMSE = 137.08
For max_depth = 5: MSE = 3904.3691496921188
For day = 0  MSE = 3904.37  and max_depth = 5 RMSE = 62.48
For day = 1  MSE = 7368.86  and max_depth = 5 RMSE = 85.84
For day = 2  MSE = 12060.61  and max_depth = 5 RMSE = 109.82
For day = 3  MSE = 19023.68  and max_depth = 5 RMSE = 137.93
For day = 4  MSE = 11164.04  and max_depth = 5 RMSE = 105.66
For max_depth = 6: MSE = 1682.6231752245399
For day = 0  MSE = 1682.62  and max_depth = 6 RMSE = 41.02
For day = 1  MSE = 4276.64  and max_depth = 6 RMSE = 65.40
For day = 2  MSE = 8153.59  and max_depth = 6 RMSE = 90.30
For day = 3  MSE = 14729.12  and max_depth = 6 RMSE = 121.36
For day = 4  MSE = 8890.57  and max_depth = 6 RMSE = 94.29
For max_depth = 7: MSE = 661.8262039410333
For day = 0  MSE = 661.83  and max_depth = 7 RMSE = 25.73
For day = 1  MSE = 3081.19  and max_depth = 7 RMSE = 55.51
For day = 2  MSE = 6776.42  and max_depth = 7 RMSE = 82.32
For day = 3  MSE = 12661.36  and max_depth = 7 RMSE = 112.52
For day = 4  MSE = 6973.01  and max_depth = 7 RMSE = 83.50
For max_depth = 8: MSE = 406.88504399061736
For day = 0  MSE = 406.89  and max_depth = 8 RMSE = 20.17
For day = 1  MSE = 2568.42  and max_depth = 8 RMSE = 50.68
For day = 2  MSE = 6064.12  and max_depth = 8 RMSE = 77.87
For day = 3  MSE = 11996.04  and max_depth = 8 RMSE = 109.53
For day = 4  MSE = 6356.28  and max_depth = 8 RMSE = 79.73
```



For question 3, I would suggest using a max_depth score of 8 since the avg RMSE is 67.59 while for max_depth = 7 mean RMSE is 71.91, max_depth = 6 mean RMSE is 82.47, max_depth = 5 mean RMSE is 100.35, max_depth = 4 mean RMSE is 133.5

[ ]: