Random Forest Task-Cleaned_MJD

October 28, 2019

1 Visualizations and Random Forest

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Prior to this task, you should have watched a video on random forest on Canvas.

1.1 Advantages of Random Forest:

- Random forest can solve both type of problems that is classification and regression and does a decent estimation at both fronts.
- Random forest can be used on both categorical and continuous variables.
- You do not have to scale features.
- Fairly robust to missing data and outliars.

1.2 Disadvantages of Random Forest

- It is complex, e.g., look at the tree at the end of this exercise! This makes it feel like a black box, and we have very little control over what the model does.
- It can take a long time to train.

[43]:
```python
# Here are some alternative ways to load packages in python as aliases
# This can be useful if you call them often
import numpy as np
import sklearn as sk
import sklearn.datasets as skd
import sklearn.ensemble as ske
import matplotlib.pyplot as plt
import pandas as pd
%matplotlib inline
```

The Boston Housing Dataset consists of price of houses in various places in Boston. Alongside with price, the dataset also provide information such as Crime (CRIM), areas of non-retail business in the town (INDUS), the age of people who own the house (AGE), and there are many other attributes that available here.

[44]:
```python
data = skd.load_boston()
df = pd.DataFrame(data.data, columns = data.feature_names)
df.head()
```

[44]:

```
       CRIM    ZN  INDUS  CHAS    NOX     RM   AGE     DIS  RAD    TAX  \
0  0.00632  18.0   2.31   0.0  0.538  6.575  65.2  4.0900  1.0  296.0
1  0.02731   0.0   7.07   0.0  0.469  6.421  78.9  4.9671  2.0  242.0
2  0.02729   0.0   7.07   0.0  0.469  7.185  61.1  4.9671  2.0  242.0
3  0.03237   0.0   2.18   0.0  0.458  6.998  45.8  6.0622  3.0  222.0
4  0.06905   0.0   2.18   0.0  0.458  7.147  54.2  6.0622  3.0  222.0

   PTRATIO       B  LSTAT
0     15.3  396.90   4.98
1     17.8  396.90   9.14
2     17.8  392.83   4.03
3     18.7  394.63   2.94
4     18.7  396.90   5.33
```

[45]:

```python
df.shape
```

[45]:

```
(506, 13)
```

[46]:

```python
print(data.DESCR)
```

```
.. _boston_dataset:

Boston house prices dataset
---------------------------

**Data Set Characteristics:**

    :Number of Instances: 506

    :Number of Attributes: 13 numeric/categorical predictive. Median Value
(attribute 14) is usually the target.

    :Attribute Information (in order):
        - CRIM     per capita crime rate by town
        - ZN       proportion of residential land zoned for lots over 25,000
sq.ft.
        - INDUS    proportion of non-retail business acres per town
        - CHAS     Charles River dummy variable (= 1 if tract bounds river; 0
otherwise)
        - NOX      nitric oxides concentration (parts per 10 million)
        - RM       average number of rooms per dwelling
        - AGE      proportion of owner-occupied units built prior to 1940
        - DIS      weighted distances to five Boston employment centres
        - RAD      index of accessibility to radial highways
        - TAX      full-value property-tax rate per $10,000
        - PTRATIO  pupil-teacher ratio by town
        - B        1000(Bk - 0.63)^2 where Bk is the proportion of blacks by
town
        - LSTAT    % lower status of the population
```

```
        - MEDV     Median value of owner-occupied homes in $1000's

    :Missing Attribute Values: None

    :Creator: Harrison, D. and Rubinfeld, D.L.

This is a copy of UCI ML housing dataset.
https://archive.ics.uci.edu/ml/machine-learning-databases/housing/


This dataset was taken from the StatLib library which is maintained at Carnegie
Mellon University.

The Boston house-price data of Harrison, D. and Rubinfeld, D.L. 'Hedonic
prices and the demand for clean air', J. Environ. Economics & Management,
vol.5, 81-102, 1978.   Used in Belsley, Kuh & Welsch, 'Regression diagnostics
...', Wiley, 1980.   N.B. Various transformations are used in the table on
pages 244-261 of the latter.

The Boston house-price data has been used in many machine learning papers that
address regression
problems.

.. topic:: References

   - Belsley, Kuh & Welsch, 'Regression diagnostics: Identifying Influential
Data and Sources of Collinearity', Wiley, 1980. 244-261.
   - Quinlan,R. (1993). Combining Instance-Based and Model-Based Learning. In
Proceedings on the Tenth International Conference of Machine Learning, 236-243,
University of Massachusetts, Amherst. Morgan Kaufmann.
```

We should check to see if there are any null values. There are several ways we've learned to do this.

[47]:
```
pd.isnull(df).any()
```

[47]:
```
CRIM       False
ZN         False
INDUS      False
CHAS       False
NOX        False
RM         False
AGE        False
DIS        False
RAD        False
TAX        False
PTRATIO    False
B          False
```

```
LSTAT      False
dtype: bool
```

We shoud check the data first to see if there are any weird anomalies.

What we should look for are: * There are not any data points that immediately appear as anomalous * No zeros in any of the measurement columns.

Another method to verify the quality of the data is make basic plots. Often it is easier to spot anomalies in a graph than in numbers.

[48]:
```
df.describe()
```

[48]:

	CRIM	ZN	INDUS	CHAS	NOX	RM
count	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000
mean	3.613524	11.363636	11.136779	0.069170	0.554695	6.284634
std	8.601545	23.322453	6.860353	0.253994	0.115878	0.702617
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000
25%	0.082045	0.000000	5.190000	0.000000	0.449000	5.885500
50%	0.256510	0.000000	9.690000	0.000000	0.538000	6.208500
75%	3.677083	12.500000	18.100000	0.000000	0.624000	6.623500
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000

	AGE	DIS	RAD	TAX	PTRATIO	B
count	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000
mean	68.574901	3.795043	9.549407	408.237154	18.455534	356.674032
std	28.148861	2.105710	8.707259	168.537116	2.164946	91.294864
min	2.900000	1.129600	1.000000	187.000000	12.600000	0.320000
25%	45.025000	2.100175	4.000000	279.000000	17.400000	375.377500
50%	77.500000	3.207450	5.000000	330.000000	19.050000	391.440000
75%	94.075000	5.188425	24.000000	666.000000	20.200000	396.225000
max	100.000000	12.126500	24.000000	711.000000	22.000000	396.900000

	LSTAT
count	506.000000
mean	12.653063
std	7.141062
min	1.730000
25%	6.950000
50%	11.360000
75%	16.955000
max	37.970000

It is useful to know whether some pairs of attributes are correlated and how much. For many ML algorithms correlated features that are not independent should be treated with caution. Here is a good blog on explaining why.

To prevent this, there are methods for deriving features that are as uncorrelated as possible (CA, ICA, autoencoder, dimensionality reduction, manifold learning, etc.), which we'll learn about in coming classes.

We can explore coreelation with Pandas pretty easily…

[49]:
```python
corr = df.corr(method = "pearson")
corr
```

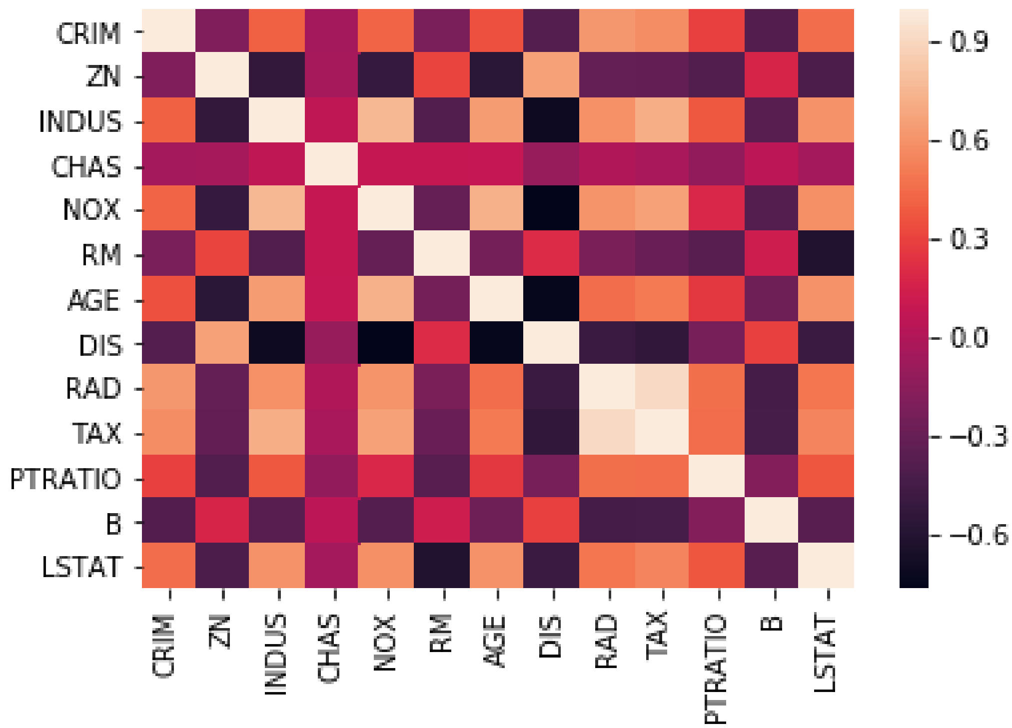
[49]:
```
             CRIM        ZN     INDUS      CHAS       NOX        RM       AGE  \
CRIM     1.000000 -0.200469  0.406583 -0.055892  0.420972 -0.219247  0.352734
ZN      -0.200469  1.000000 -0.533828 -0.042697 -0.516604  0.311991 -0.569537
INDUS    0.406583 -0.533828  1.000000  0.062938  0.763651 -0.391676  0.644779
CHAS    -0.055892 -0.042697  0.062938  1.000000  0.091203  0.091251  0.086518
NOX      0.420972 -0.516604  0.763651  0.091203  1.000000 -0.302188  0.731470
RM      -0.219247  0.311991 -0.391676  0.091251 -0.302188  1.000000 -0.240265
AGE      0.352734 -0.569537  0.644779  0.086518  0.731470 -0.240265  1.000000
DIS     -0.379670  0.664408 -0.708027 -0.099176 -0.769230  0.205246 -0.747881
RAD      0.625505 -0.311948  0.595129 -0.007368  0.611441 -0.209847  0.456022
TAX      0.582764 -0.314563  0.720760 -0.035587  0.668023 -0.292048  0.506456
PTRATIO  0.289946 -0.391679  0.383248 -0.121515  0.188933 -0.355501  0.261515
B       -0.385064  0.175520 -0.356977  0.048788 -0.380051  0.128069 -0.273534
LSTAT    0.455621 -0.412995  0.603800 -0.053929  0.590879 -0.613808  0.602339

              DIS       RAD       TAX   PTRATIO         B     LSTAT
CRIM    -0.379670  0.625505  0.582764  0.289946 -0.385064  0.455621
ZN       0.664408 -0.311948 -0.314563 -0.391679  0.175520 -0.412995
INDUS   -0.708027  0.595129  0.720760  0.383248 -0.356977  0.603800
CHAS    -0.099176 -0.007368 -0.035587 -0.121515  0.048788 -0.053929
NOX     -0.769230  0.611441  0.668023  0.188933 -0.380051  0.590879
RM       0.205246 -0.209847 -0.292048 -0.355501  0.128069 -0.613808
AGE     -0.747881  0.456022  0.506456  0.261515 -0.273534  0.602339
DIS      1.000000 -0.494588 -0.534432 -0.232471  0.291512 -0.496996
RAD     -0.494588  1.000000  0.910228  0.464741 -0.444413  0.488676
TAX     -0.534432  0.910228  1.000000  0.460853 -0.441808  0.543993
PTRATIO -0.232471  0.464741  0.460853  1.000000 -0.177383  0.374044
B        0.291512 -0.444413 -0.441808 -0.177383  1.000000 -0.366087
LSTAT   -0.496996  0.488676  0.543993  0.374044 -0.366087  1.000000
```

1.2.1 Let's explore/review some visualization approaches

A good way to look at correlations quickly is a visualization called a heatmap. Let's take a look at correlations betewen features in our dataset.

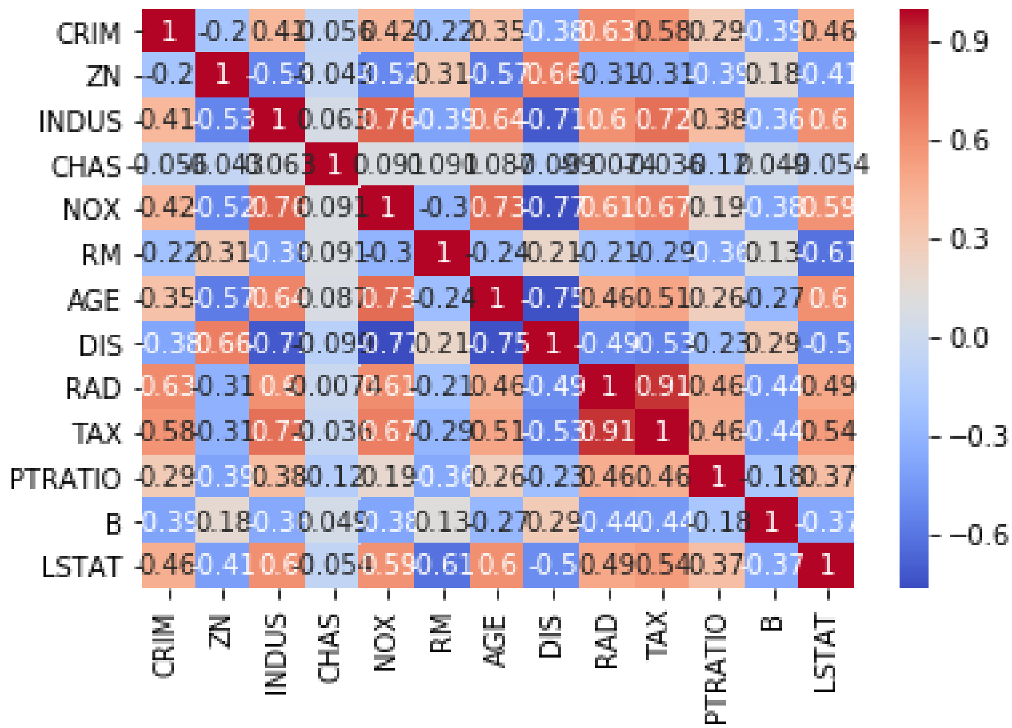
[50]:
```python
import seaborn as sns
sns.heatmap(corr)
```

[50]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1e454e555c0>
```



You can also save the plots you make in these notebooks locally.

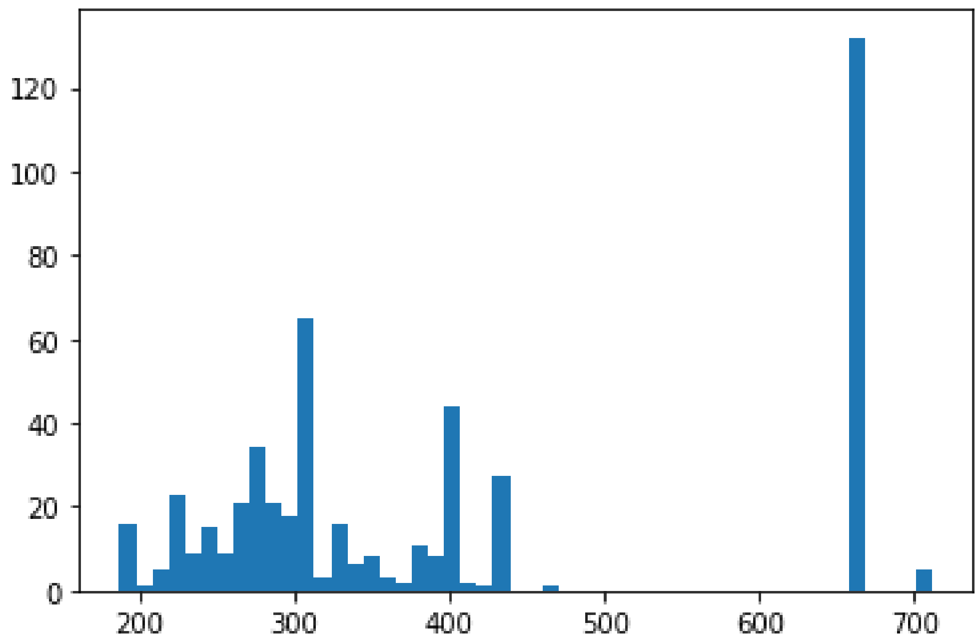
[51]:
```
sns.heatmap(corr, annot=True, cmap='coolwarm')
plt.savefig('heatmap.png', tight_layout=True)
```



Let's take a look how we can explore the distributions of values within a specific feature. Specifically, let's look at the distribution of property tax in Boston. We can do this either in matplotlib or sns. There are so many tools available to you in Python!

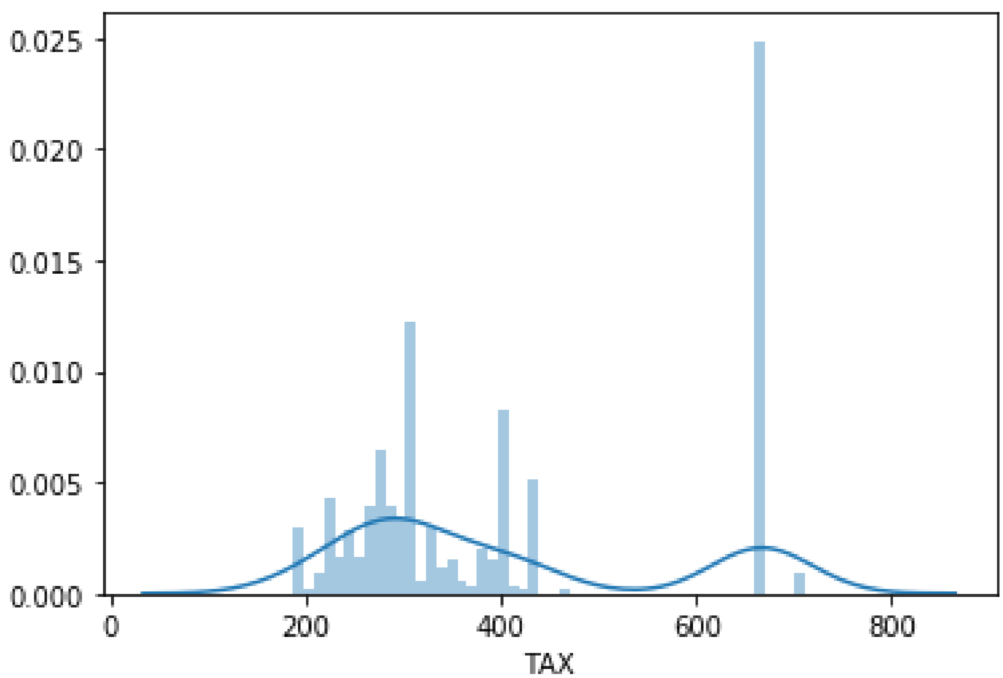
[52]:
```
attr = df['TAX']
plt.hist(attr, bins=50)
```

[52]:
```
(array([ 16.,   1.,   5.,  23.,   9.,  15.,   9.,  21.,  34.,  21.,  18.,
         65.,   3.,  16.,   6.,   8.,   3.,   2.,  11.,   8.,  44.,   2.,
          1.,  27.,   0.,   0.,   1.,   0.,   0.,   0.,   0.,   0.,   0.,
          0.,   0.,   0.,   0.,   0.,   0.,   0.,   0.,   0.,   0.,   0.,
          0., 132.,   0.,   0.,   0.,   5.]),
 array([187.  , 197.48, 207.96, 218.44, 228.92, 239.4 , 249.88, 260.36,
        270.84, 281.32, 291.8 , 302.28, 312.76, 323.24, 333.72, 344.2 ,
        354.68, 365.16, 375.64, 386.12, 396.6 , 407.08, 417.56, 428.04,
        438.52, 449.  , 459.48, 469.96, 480.44, 490.92, 501.4 , 511.88,
        522.36, 532.84, 543.32, 553.8 , 564.28, 574.76, 585.24, 595.72,
        606.2 , 616.68, 627.16, 637.64, 648.12, 658.6 , 669.08, 679.56,
        690.04, 700.52, 711.  ]),
 <a list of 50 Patch objects>)
```



[53]:
```
sns.distplot(attr,bins = 50)
```

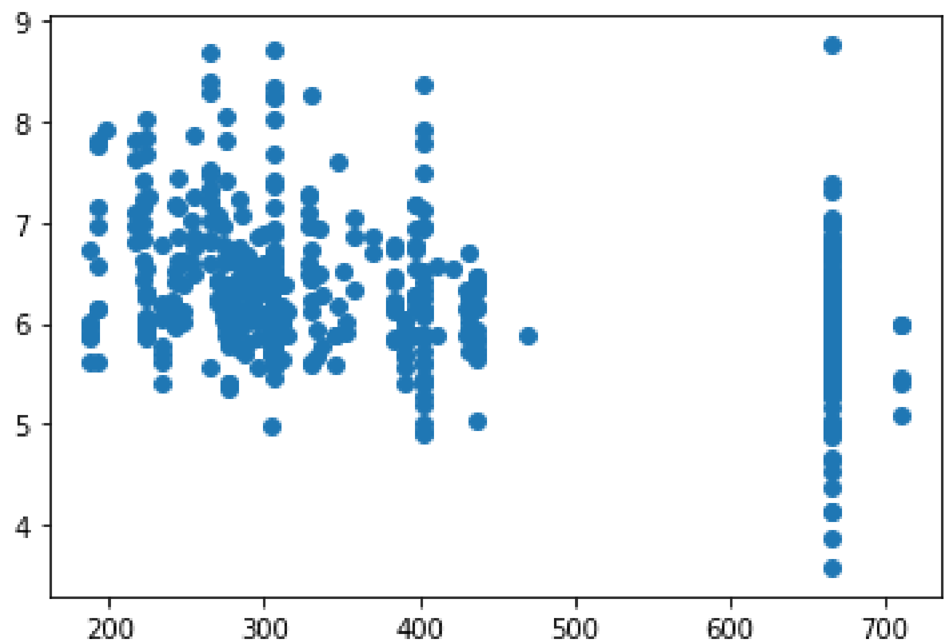
[53]: <matplotlib.axes._subplots.AxesSubplot at 0x1e453dd91d0>



What's the correlation between property taxes and the number of rooms in a house?

[54]:
```
plt.scatter(df['TAX'],df['RM'])
```

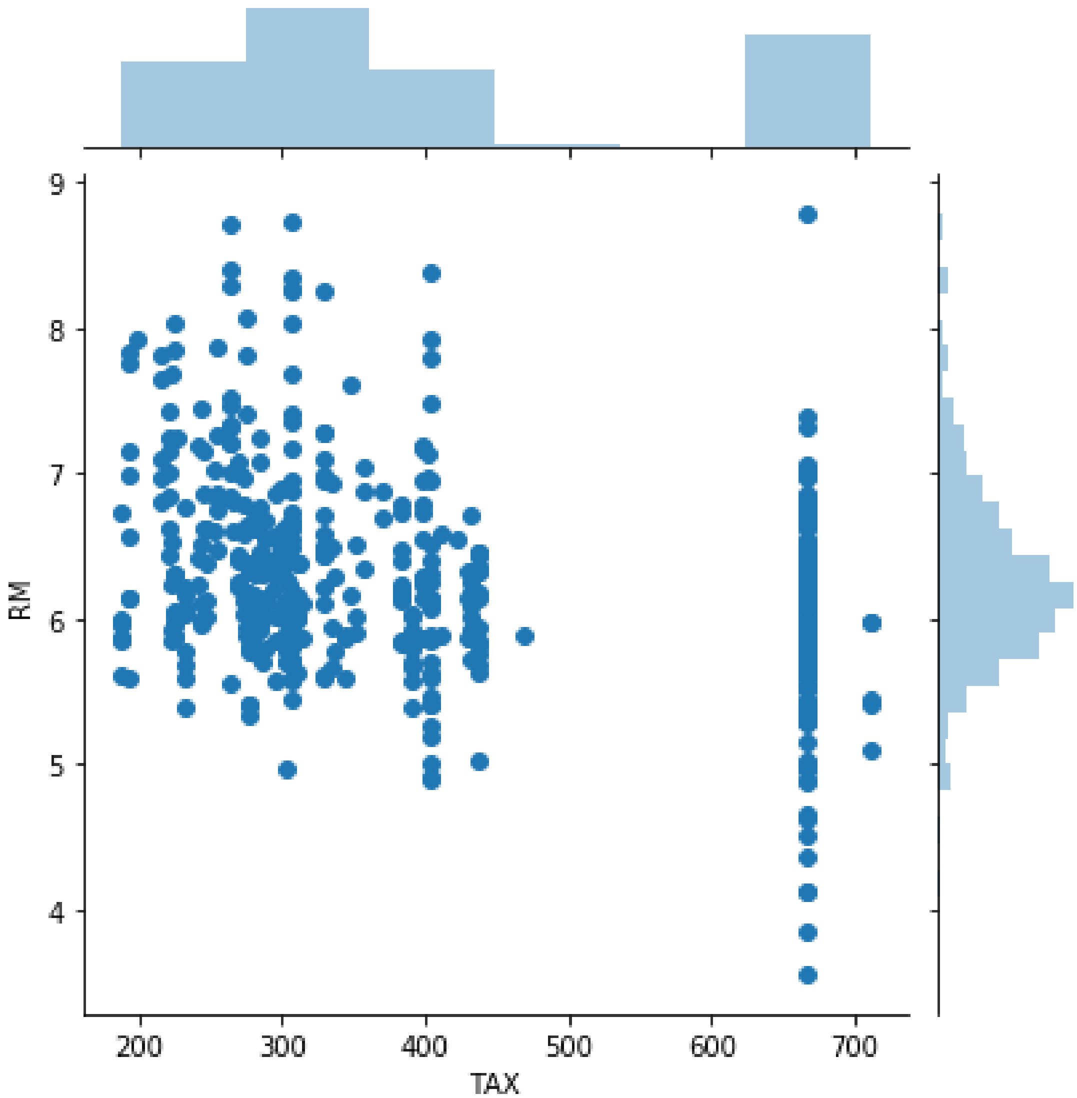
[54]: `<matplotlib.collections.PathCollection at 0x1e4551bfa58>`



Another possibility is to aggregate data points over 2D areas and estimate the probability desnsity function. Its a 2D generalization of a histogram. We can either use a rectangular grid, or even a hexagonal one.

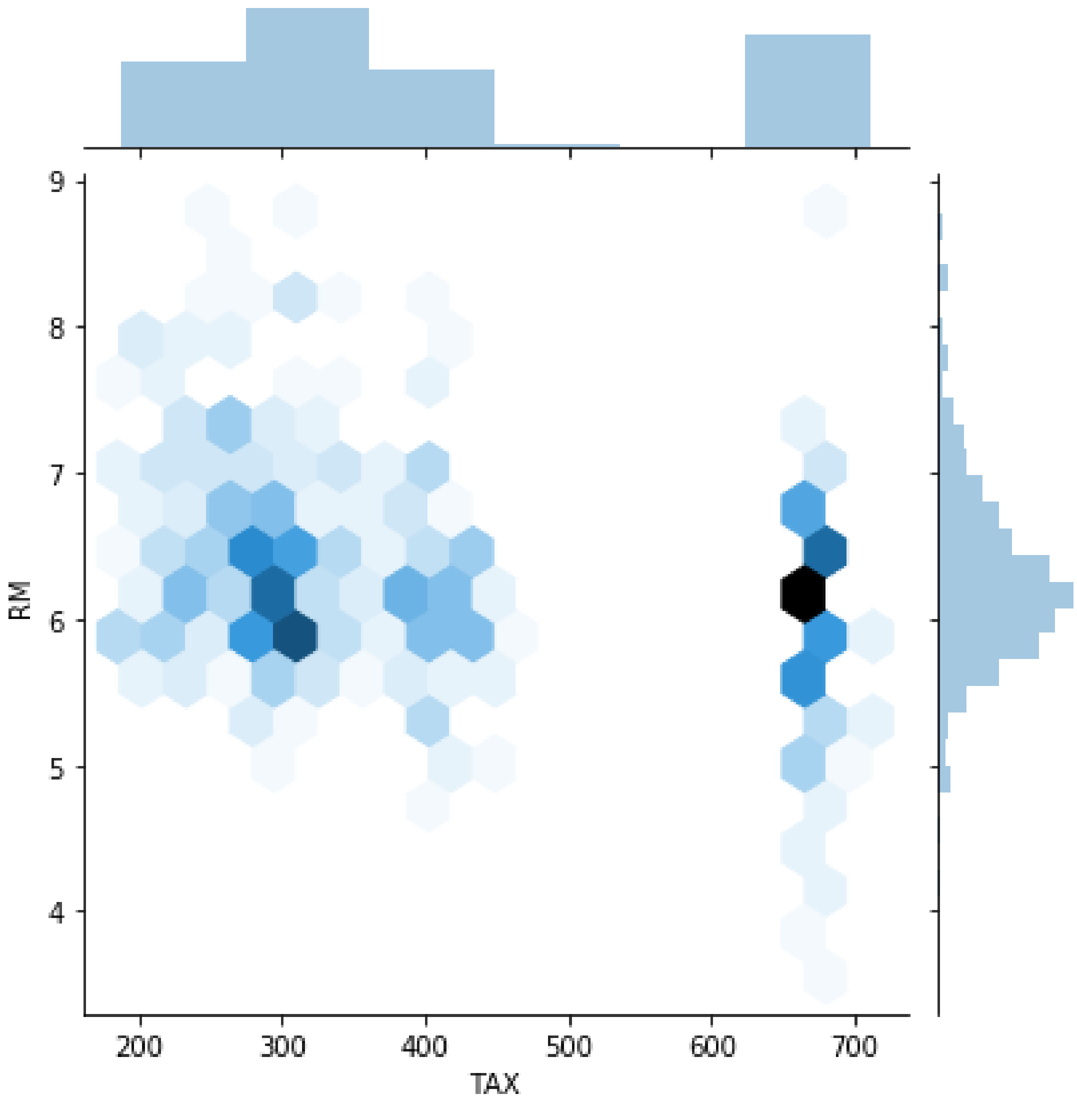
[55]:
```
sns.jointplot(df['TAX'],df['RM'],kind = 'scatter')
```

[55]: `<seaborn.axisgrid.JointGrid at 0x1e455178208>`



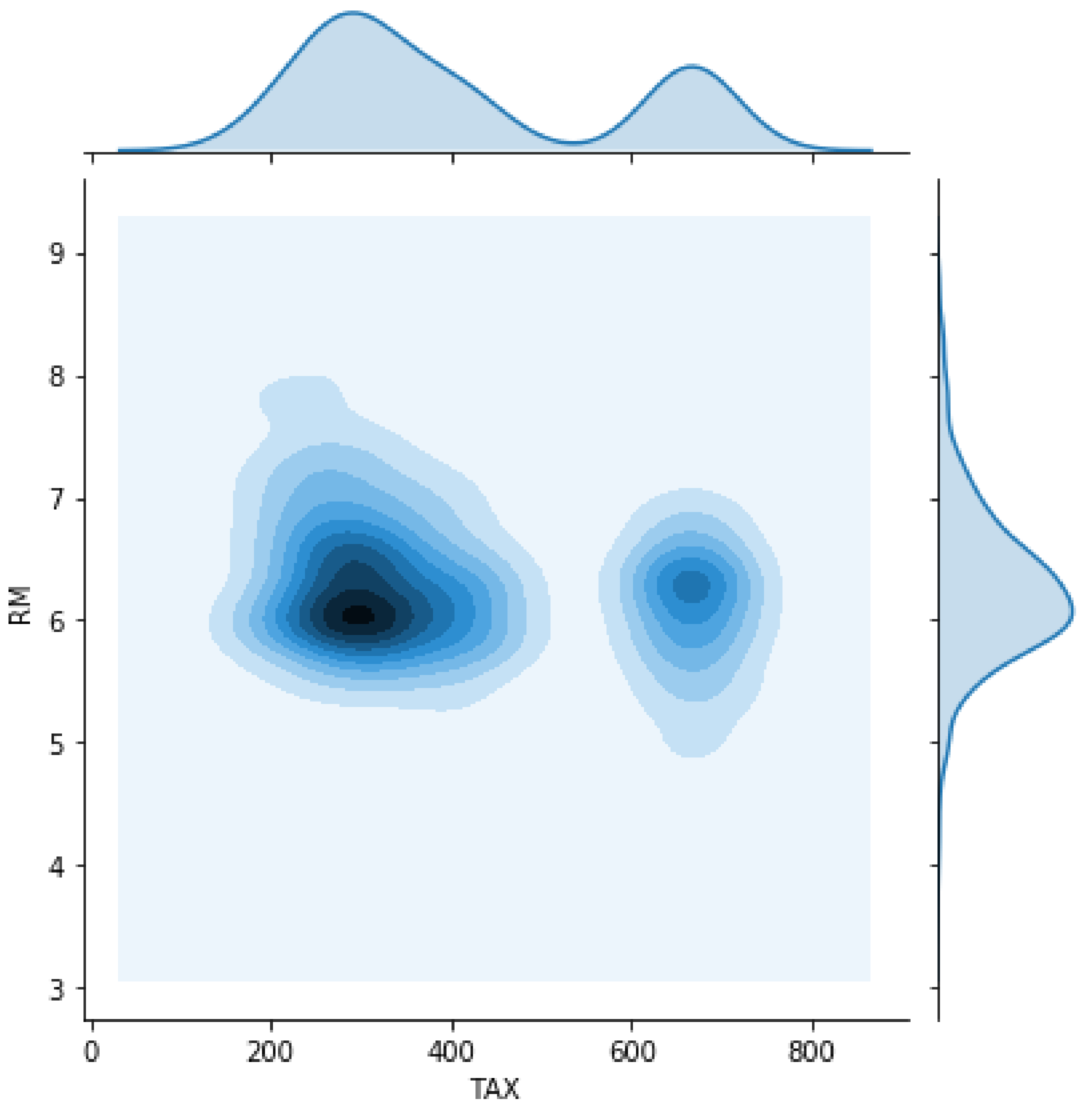
[56]:
```
sns.jointplot(df['TAX'],df['RM'],kind = 'hex')
```

[56]: `<seaborn.axisgrid.JointGrid at 0x1e4552fc080>`



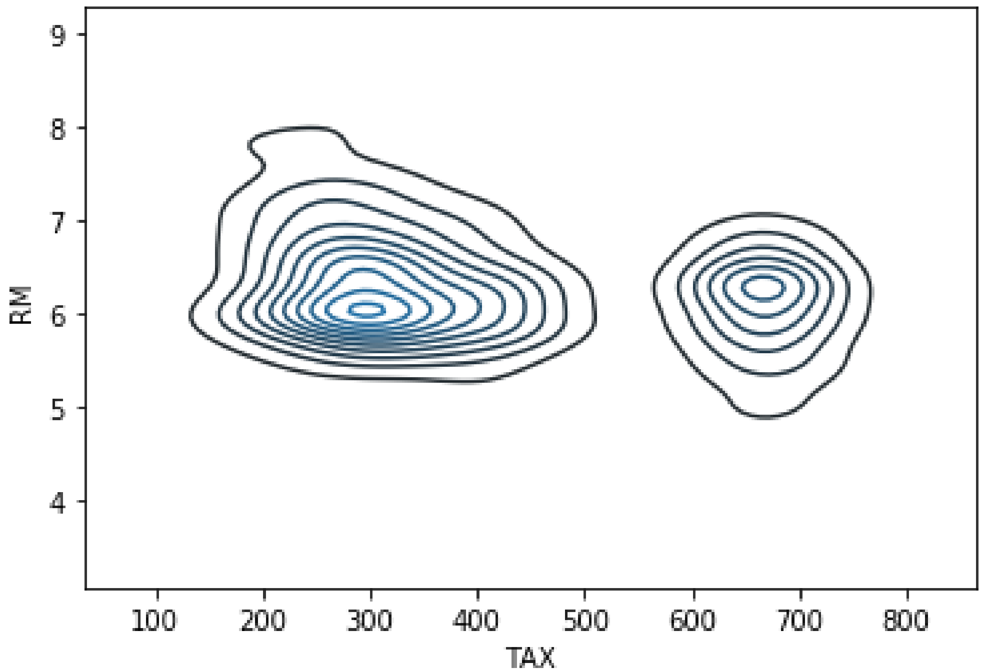
[57]:
```
sns.jointplot(df['TAX'],df['RM'],kind = 'kde')
```

[57]: <seaborn.axisgrid.JointGrid at 0x1e455461198>



[58]:
```
sns.kdeplot(df['TAX'],df['RM'])
```

[58]: <matplotlib.axes._subplots.AxesSubplot at 0x1e45557c2b0>



What you'll see is you have access to so many visualizations. A great way to explore them is through the gallery: https://seaborn.pydata.org/examples/index.html

2 How to implement Random Forest

First, we need to get a train and test dataset going...

[59]:
```
from sklearn.model_selection import train_test_split
X = df
```

[60]:
```
Y = data.target
```

[61]:
```
X.shape
```

[61]:
```
(506, 13)
```

[62]:
```
Y.shape
```

[62]:
```
(506,)
```

The 'ravel' command flattens an array: "ravel(): when you have y.shape == (10, 1), using y.ravel().shape == (10,). In words... it flattens an array."

https://stackoverflow.com/questions/34165731/a-column-vector-y-was-passed-when-a-1d-array-was-expected

[63]:
```
X_train, X_test, Y_train, Y_test = train_test_split(X,Y, test_size = 0.25,␣
↪random_state = 0)
```

[64]:
```
print(X_train.shape,Y_train.shape)
```

```
(379, 13) (379,)
```

[65]:
```
reg = ske.RandomForestRegressor(n_estimators=1000,random_state = 0)
```

[66]:
```
Y_train = np.ravel(Y_train)
```

[67]:
```
reg.fit(X_train, Y_train)
```

[67]:
```
RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=None,
                      max_features='auto', max_leaf_nodes=None,
                      min_impurity_decrease=0.0, min_impurity_split=None,
                      min_samples_leaf=1, min_samples_split=2,
                      min_weight_fraction_leaf=0.0, n_estimators=1000,
                      n_jobs=None, oob_score=False, random_state=0, verbose=0,
                      warm_start=False)
```

[68]:
```
Y_pred = reg.predict(X_test)
```

How do we evaluate this model? Previously, we've worked with labels for classifications but now instead of a DISCRETE target, we've got a continuous target. For example, the confusion matrix doesn't make sense and the code will error out below:

[69]:
```
from sklearn.metrics import confusion_matrix

confusion_matrix(Y_test, Y_pred)
```

```
      ␣
↪---------------------------------------------------------------------------

     ValueError                                Traceback (most recent call␣
↪last)

     <ipython-input-69-237cb7848c80> in <module>
       1 from sklearn.metrics import confusion_matrix
       2
 ----> 3 confusion_matrix(Y_test, Y_pred)


      ␣
↪~\AppData\Local\Continuum\anaconda3\lib\site-packages\sklearn\metrics\classification.
↪py in confusion_matrix(y_true, y_pred, labels, sample_weight)
     251
     252     """
 --> 253     y_type, y_true, y_pred = _check_targets(y_true, y_pred)
     254     if y_type not in ("binary", "multiclass"):
     255         raise ValueError("%s is not supported" % y_type)
```

```
↪~\AppData\Local\Continuum\anaconda3\lib\site-packages\sklearn\metrics\classification.
↪py in _check_targets(y_true, y_pred)
     86     # No metrics support "multiclass-multioutput" format
     87     if (y_type not in ["binary", "multiclass",
↪"multilabel-indicator"]):
---> 88         raise ValueError("{0} is not supported".format(y_type))
     89
     90     if y_type in ["binary", "multiclass"]:


ValueError: continuous is not supported
```

Check out this documentation and see if you can find some ways to evaluate this model.

[ ]:
```
from sklearn.metrics import explained_variance_score, max_error,
↪mean_absolute_error,mean_squared_error,r2_score
```

[ ]:
```
explained_variance_score(Y_test,Y_pred)
```

[ ]:
```
max_error(Y_test,Y_pred)
```

[70]:
```
print(mean_absolute_error(Y_test,Y_pred))
print(mean_squared_error(Y_test,Y_pred))
print(r2_score(Y_test, Y_pred, multioutput='variance_weighted'))
```

```
2.5419283464567104
16.427632250630026
0.7989249666895868
```

The importance of our features can be found in reg.feature_importances_. We sort them by decreasing order of importance:

[71]:
```
reg.feature_importances_
```

[71]:
```
array([0.03802909, 0.00096075, 0.00795783, 0.00118918, 0.0158759 ,
       0.39465879, 0.01264835, 0.04119215, 0.00404612, 0.01747215,
       0.02039368, 0.0102544 , 0.43532161])
```

[72]:
```
feat_ind = np.argsort(reg.feature_importances_)[::-1]
```

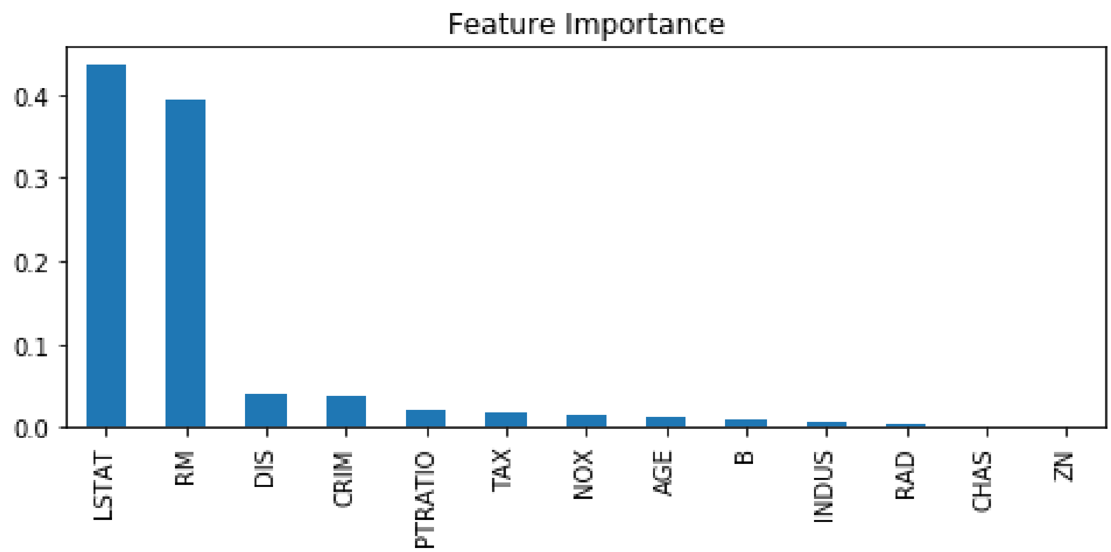
[73]:
```
feat_imp = reg.feature_importances_[np.argsort(reg.feature_importances_)][::-1]
```

[74]:
```
data['feature_names'][feat_ind]
```

[74]:
```
array(['LSTAT', 'RM', 'DIS', 'CRIM', 'PTRATIO', 'TAX', 'NOX', 'AGE', 'B',
       'INDUS', 'RAD', 'CHAS', 'ZN'], dtype='<U7')
```

[75]:
```
fig,ax=plt.subplots(1,1,figsize = (8,3))
labels = data['feature_names'][feat_ind]
pd.Series(feat_imp,index = labels).plot('bar',ax = ax)
ax.set_title('Feature Importance')
```

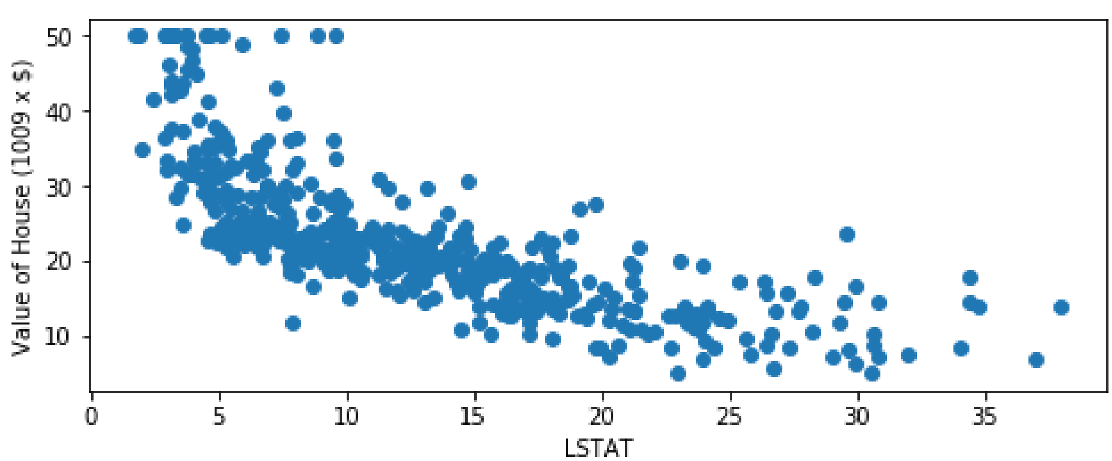
[75]: Text(0.5, 1.0, 'Feature Importance')



We can compute how much each feature contributes to decreasing the weighted impurity within a tree. This is a fast calculation, but one should be cautious because it can be a biased approach. It has a tendency to inflate the importance of continuous features or high-cardinality categorical variables (a lot of very uncommon or unique variables).

[76]:
```
fig,ax=plt.subplots(1,1,figsize = (8,3))
ax.scatter(X['LSTAT'],Y)
ax.set_xlabel('LSTAT')
ax.set_ylabel('Value of House (1009 x $)')
```

[76]: Text(0, 0.5, 'Value of House (1009 x $)')



[77]:
```
from sklearn import tree
```

[78]:
```
reg.estimators_[0]
```

[78]:
```
DecisionTreeRegressor(criterion='mse', max_depth=None, max_features='auto',
                      max_leaf_nodes=None, min_impurity_decrease=0.0,
                      min_impurity_split=None, min_samples_leaf=1,
                      min_samples_split=2, min_weight_fraction_leaf=0.0,
                      presort=False, random_state=209652396, splitter='best')
```

[79]:
```
tree.export_graphviz(reg.estimators_[0], 'tree.dot')
```

[80]:
```
tree.export_graphviz(reg.estimators_[5], 'tree.dot', feature_names =␣
 ↪data['feature_names'], rounded = True, precision = 1)
```

You'll need to open tree.dot file in a text editor, e.g., notepad. Select all the code and paste in here: http://www.webgraphviz.com/. Scroll right and the tree should show up.

2.1 More practice - optional but recommended because its interesting and doesn't take too long

This is another good tutorial on random forest: . You can perform this tutorial on your own and expand it for your choose your adventure, though you should be sure to demonstrate knowledge of this topic vs. copying and executing the tutorial.