main

March 28, 2019

1 Data Analytics ECS784P

1.1 London House Price Data Analysis and Prediction

1.1.1 Machine Learning of London house price data based on features in yearly data ranging 1995-2018:

- House Price
- House Sales Volume
- House Price Index
- Bank Rate (England)
- GDP (UK)
- GDP Growth (UK)
- Total number household
- Affordability (House price to residence-based earnings ratio)
- Median Income

We are using LinearRegression and GradientBoostingRegressionTree as our methods witht the implementation of ShuffleSPlit cross-validation along with GridSearchCV for parameters tuning.

1.1.2 Load the data

JS code to prevent sub/scrollable window inside the notebook

```
In [1]: %%javascript
        IPython.OutputArea.prototype._should_scroll = function(lines) {
            return false;
        }
```

```
<IPython.core.display.Javascript object>
```

Import external libraries

```
In [2]: import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        import seaborn as sns
        import mpl_toolkits
```

```
from sklearn import preprocessing, model_selection, metrics, svm, ensemble
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import ShuffleSplit, train_test_split, GridSearchCV, lear
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.naive_bayes import GaussianNB
from sklearn.decomposition import PCA
from IPython.display import HTML
from scipy import sparse
from pprint import pprint

%matplotlib inline
```

HTML and JS code to implement toggle to hide or show warning messages that might come up in notebook

```
In [3]: HTML('''<script>
        code_show_err=false;
        function code_toggle_err() {
         if (code_show_err){
         $('div.output_stderr').hide();
         } else {
         $('div.output_stderr').show();
         }
         code_show_err = !code_show_err
        }
        $( document ).ready(code_toggle_err);
        </script>
        To toggle on/off Warning Message, click <a href="javascript:code_toggle_err()">here</a
```

```
Out[3]: <IPython.core.display.HTML object>
```

```
In [4]: # get the data from csv and set it to variable 'data'
        data = pd.read_csv('data_year_preprocessed.csv')
        data = data.set_index('year')
```

```
In [5]: # peek the data
        data
```

```
Out[5]:              price  salesVolume  indexPrice    rate      gdp  gdpGrowth  \
        year
        1995   74721.32688     106850.0   18.548293  6.3750  1336125      0.025
        1996   78166.22435     132953.0   19.403430  5.9375  1410855      0.025
        1997   89943.92010     154343.0   22.327042  7.2500  1553949      0.043
        1998  102110.61160     145942.0   25.347216  6.2500  1641822      0.033
        1999  115686.25990     169076.0   28.717139  5.5000  1668683      0.032
        2000  142006.69330     149269.0   35.250737  6.0000  1651392      0.035
        2001  159225.79230     162744.0   39.525084  4.0000  1626218      0.028
        2002  187395.75390     173993.0   46.517796  4.0000  1775814      0.025
        2003  211100.92160     153784.0   52.402199  3.7500  2045693      0.033
```

```
2004  228614.03650     163797.0   56.749531  4.7500  2404700       0.023
2005  235329.26910     136836.0   58.416472  4.5000  2527843       0.031
2006  251281.17760     171450.0   62.376261  5.0000  2700951       0.025
2007  287114.01550     165571.0   71.271151  5.5000  3085300       0.025
2008  282959.01210      80921.0   70.239743  2.0000  2934747      -0.003
2009  257853.75650      75231.0   64.007792  0.5000  2403357      -0.042
2010  284543.12810      91933.0   70.632972  0.5000  2455309       0.017
2011  290551.08050      90041.0   72.124344  0.5000  2635799       0.016
2012  303927.32910      93988.0   75.444769  0.5000  2677082       0.014
2013  329167.88190     115459.0   81.710306  0.5000  2755356       0.020
2014  386124.33550     126356.0   95.848773  0.5000  3036310       0.029
2015  425134.16170     120358.0  105.532298  0.5000  2897060       0.023
2016  467502.88020     104805.0  116.049616  0.2500  2660687       0.018
2017  480240.15790      96023.0  119.211428  0.5000  2622434       0.018
2018  478444.51250          NaN  118.765689  0.7500  2822817       0.014

      numberHousehold  affordability  medianincome
year
1995      2869079.452            NaN   15247.90251
1996      2887000.000            NaN   15709.96016
1997      2855900.000            NaN   16114.26061
1998      2872500.000            NaN   16114.26061
1999      2901200.000            NaN   16114.26061
2000      2923900.000            NaN   16600.00000
2001      2963800.000            NaN   17600.00000
2002      2971400.000           6.90   18500.00000
2003      2979500.000           7.44   18800.00000
2004      2963300.000           7.95   19100.00000
2005      2999900.000           8.09   19000.00000
2006      3000900.000           8.37   20300.00000
2007      3004200.000           8.38   20800.00000
2008      3062600.000           8.52   21800.00000
2009      3085300.000           7.83   21178.67066
2010      3090300.000           8.75   23400.00000
2011      3180600.000           9.18   23300.00000
2012      3188600.000           9.15   23800.00000
2013      3210300.000           9.62   24600.00000
2014      3225000.000          10.77   25600.00000
2015      3253000.000          11.78   26400.00000
2016      3276400.000          12.91   27200.00000
2017      3285400.000          13.24   27900.00000
2018      3305793.546            NaN   28716.39332
```

In [6]:
```
# brief statistical description of each column
data.describe()
```

Out[6]:
```
             price   salesVolume  indexPrice       rate           gdp  \
count    24.000000     23.000000   24.000000  24.000000  2.400000e+01
```

```
mean    256214.343276  129640.130435   63.600837   3.158854  2.305429e+06
std     126337.486812   32256.222907   31.361126   2.511183  5.698118e+05
min      74721.326880   75231.000000   18.548293   0.250000  1.336125e+06
25%     154921.017550  100414.000000   38.456497   0.500000  1.664360e+06
50%     254567.467050  132953.000000   63.192027   3.875000  2.491576e+06
75%     310237.467300  158543.500000   77.011153   5.500000  2.714552e+06
max     480240.157900  173993.000000  119.211428   7.250000  3.085300e+06

        gdpGrowth  numberHousehold  affordability  medianincome
count   24.000000     2.400000e+01      16.000000     24.000000
mean     0.021125     3.056495e+06       9.305000  20995.654520
std      0.016276     1.485513e+05       1.902546   4228.612122
min     -0.042000     2.855900e+06       6.900000  15247.902510
25%      0.017750     2.953450e+06       8.055000  17350.000000
50%      0.025000     3.002550e+06       8.635000  20550.000000
75%      0.029500     3.194025e+06       9.907500  24000.000000
max      0.043000     3.305794e+06      13.240000  28716.393320
```

In [7]:
```
# checking which of the columns have missing values which indicated by any number > 0
data.isnull().sum()
```

Out[7]:
```
price              0
salesVolume        1
indexPrice         0
rate               0
gdp                0
gdpGrowth          0
numberHousehold    0
affordability      8
medianincome       0
dtype: int64
```

1.2 Data Cleaning

- Fill salesVolume missing values based on a randomized values calculated from its mean and standard deviation

The inputed values will be based in the range of (mean - std) to (mean +std)

In [8]:
```
salesVolume_avg = data['salesVolume'].mean()
salesVolume_std = data['salesVolume'].std()
salesVolume_null_count = data['salesVolume'].isnull().sum()
salesVolume_null_random_list = np.random.randint(salesVolume_avg - salesVolume_std, sal
data['salesVolume'][np.isnan(data['salesVolume'])] = salesVolume_null_random_list
data['salesVolume'] = data['salesVolume'].astype(int)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame
```

```
See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html
  """
```

- Fill affordability missing values based on a randomized values calculated from its minimum value and standard deviation

The reason being is that the affordability is keep growing year by year, so we assume that the missing values which in this case is mostly the data before 2002 will be inputed by randomizing values between the range of (min - std) to (min) For the value of 2018, We used the 2017 value using the fillna function that pandas library provided using the parameter of method='ffill'

```
In [9]: data['affordability'].fillna(method='ffill',inplace=True)
        affordability_avg = data['affordability'].mean()
        affordability_std = data['affordability'].std()
        affordability_min = data['affordability'].min()
        affordability_null_count = data['affordability'].isnull().sum()
        affordability_null_random_list = np.random.randint(affordability_min - affordability_st
        data['affordability'][np.isnan(data['affordability'])] = affordability_null_random_lis
        data['affordability'] = data['affordability'].astype(int)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:7: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html
  import sys
```

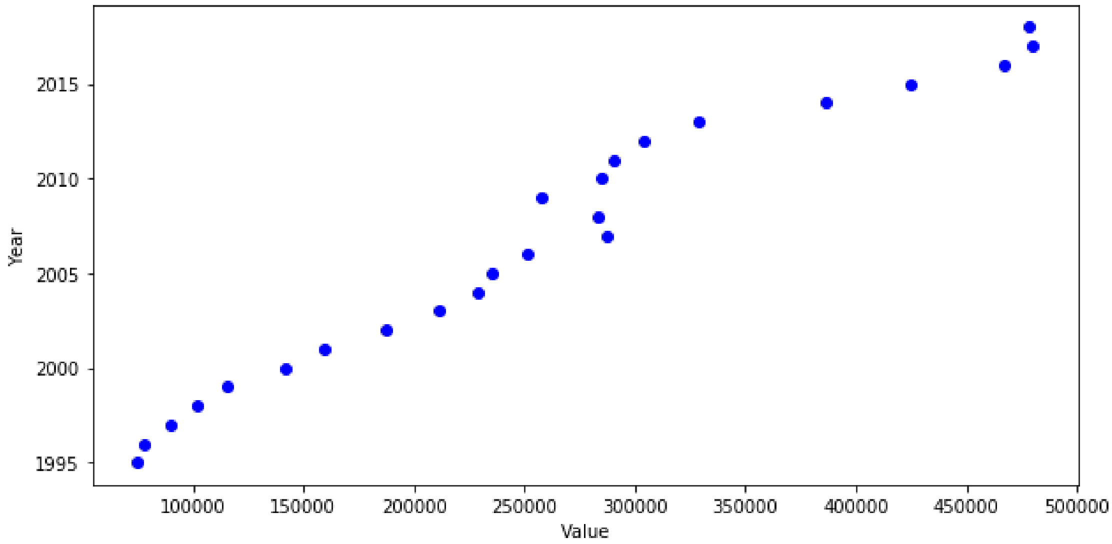
```
In [10]: # Double checking which of the columns have missing values which indicated by any num
         data.isnull().sum()
```

```
Out[10]: price              0
         salesVolume        0
         indexPrice         0
         rate               0
         gdp                0
         gdpGrowth          0
         numberHousehold    0
         affordability      0
         medianincome       0
         dtype: int64
```

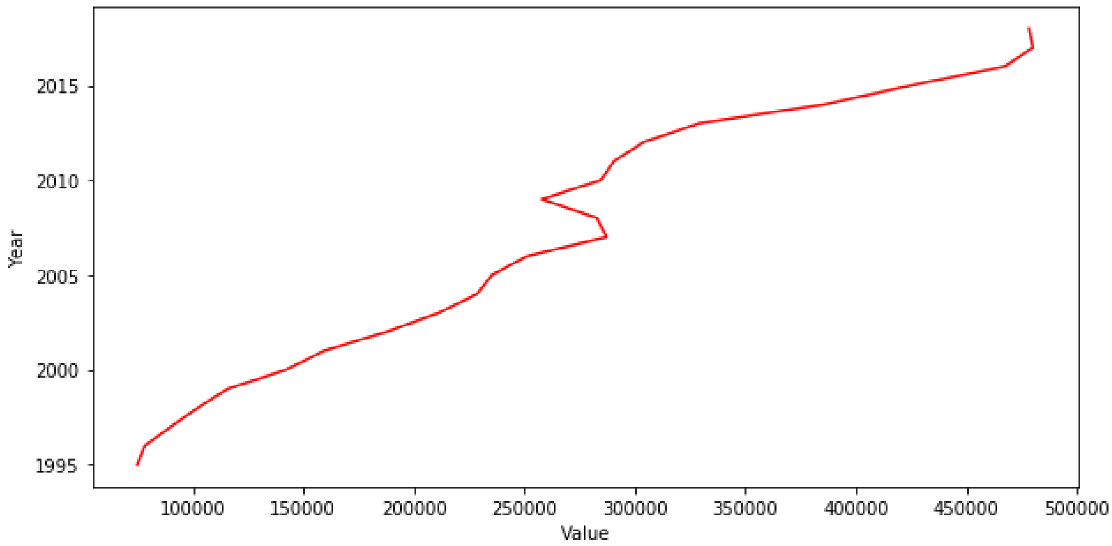
1.2.1 Data Visualisation

- Plot data to visualize the values of house price, sales volume, gdp, and number household each year.
- Visualize a correlation matrix between each feature to get a better understanding of feature importance

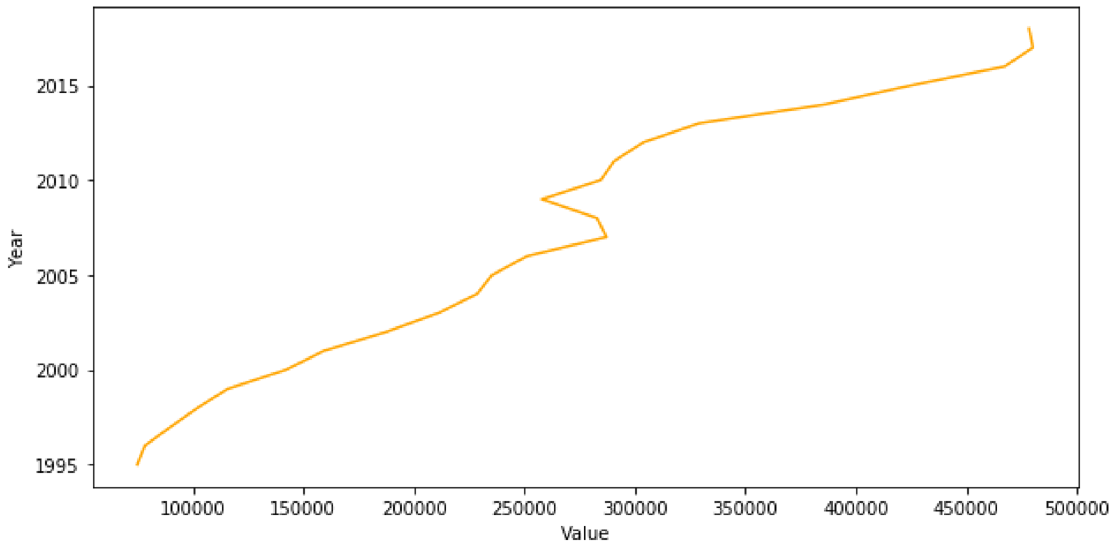
```
In [11]: # plot data
         fig, ax = plt.subplots(figsize=(10, 5))
         ax.scatter(data.price,data.index, color="b", label="House Price")
         ax.set_xlabel("Value")
         ax.set_ylabel("Year")
         plt.show()
```



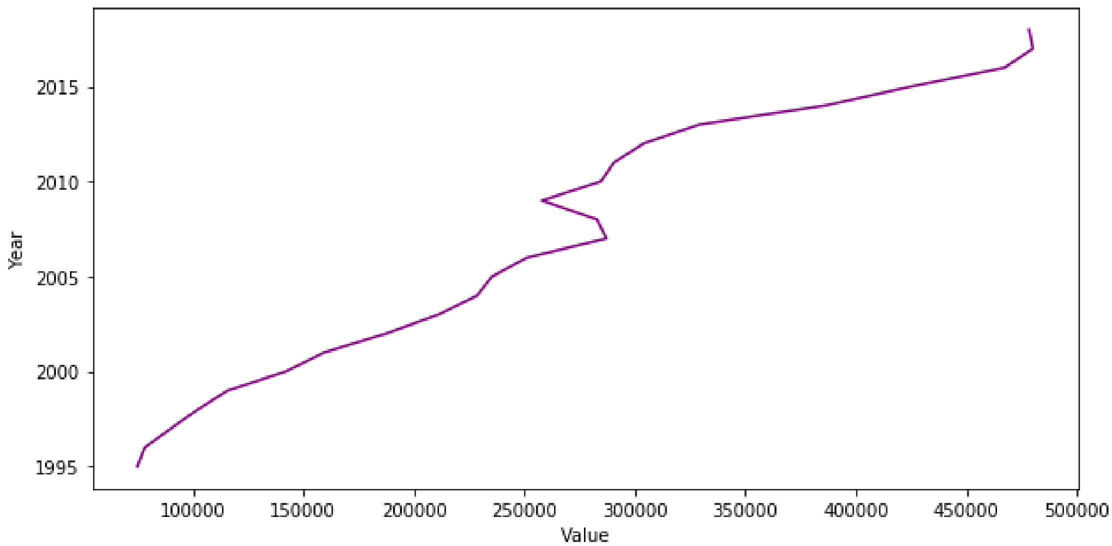

```
In [12]: fig, ax = plt.subplots(figsize=(10, 5))
         ax.plot(data.price,data.index, color="r", label="salesVolume")
         ax.set_xlabel("Value")
         ax.set_ylabel("Year")
         plt.show()
```



```
In [13]: fig, ax = plt.subplots(figsize=(10, 5))
         ax.plot(data.price,data.index, color="orange", label="GDP")
         ax.set_xlabel("Value")
         ax.set_ylabel("Year")
         plt.show()
```

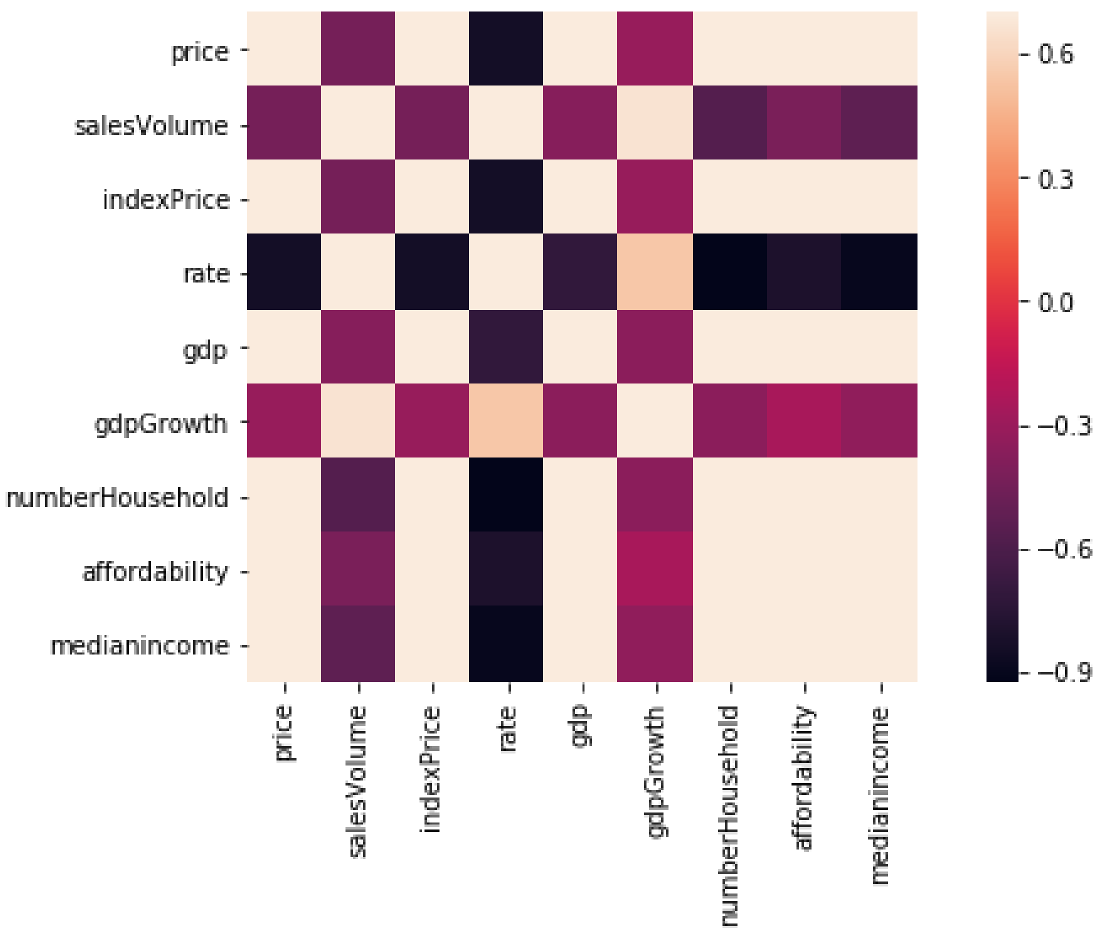



```
In [14]: fig, ax = plt.subplots(figsize=(10, 5))
         ax.plot(data.price,data.index, color="purple", label="numberHousehold")
         ax.set_xlabel("Value")
         ax.set_ylabel("Year")
         plt.show()
```



```
In [15]: # Build the correlation matrix
         matrix = data.corr()
         f, ax = plt.subplots(figsize=(10, 5))
         sns.heatmap(matrix, vmax=0.7, square=True)
```

```
Out[15]: <matplotlib.axes._subplots.AxesSubplot at 0x236d19ab630>
```



Data Preparation/Allocation

- Preparing Data by separating them into training and target (test) tables

```
In [16]: # allocate all columns beside price as the training table 'train1' which will be the
         train1 = data.drop(['price'],axis=1)
```

```
In [17]: # allocate price column as target table which will be the test
         target = data['price']
```

1.3 Methodology

- Gradient Boosted Regression Trees

Gradient Boosted Regression Trees (GBRT) or shorter Gradient Boosting is a flexible non-parametric statistical learning technique for classification and regression. - Linear Regression

One of the simplest model of supervised learning which assumed that the dependent variable (House Price) varies linearly with the independent variable(s) (House Sales Volume, Income, etc). Essentially fitting a straight line through the data and expecting it to give us a good prediction for values we haven't seen.

The idea of building a model is to minimize this error so that when we make a new prediction we can do so with utmost confidence (~95% is a good benchmark). There are multiple ways of minimizing this error, simplest being the least-squares method. In other words, calculating the sum of squares of each error (to eliminate negatives) and minimizing this number.

Linear Regression

```
In [18]: reg = LinearRegression()
```

```
In [19]: # split the data 90% as train 10% as test
         x_train , x_test , y_train , y_test = train_test_split(train1 , target , test_size = (
```

```
In [20]: reg.fit(x_train,y_train)
```

```
Out[20]: LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
                  normalize=False)
```

```
In [21]: reg.score(x_test,y_test)
```

```
Out[21]: 0.9999999999999996
```

As we can see from the result of the LinearRegression score (~99%) which means that its way over-fitting. In order to resolve this issue, we implemented a second method, GBRT while also using GridSearchCV method to tune the parameters.

Gradient Boosting

```
In [22]: #split the data
         X_train, X_test, y_train, y_test = train_test_split(train1, target, test_size = 0.10,r
```

```
In [23]: gbrt=GradientBoostingRegressor(n_estimators=10)
         gbrt.fit(X_train, y_train)
```

```
Out[23]: GradientBoostingRegressor(alpha=0.9, criterion='friedman_mse', init=None,
                      learning_rate=0.1, loss='ls', max_depth=3, max_features=None,
                      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=10, n_iter_no_change=None, presort='auto',
                      random_state=None, subsample=1.0, tol=0.0001,
                      validation_fraction=0.1, verbose=0, warm_start=False)
```

A simple table to show the result of feature importances based on gbrt

```
In [24]: importances = gbrt.feature_importances_
         std = np.std([gbrt.feature_importances_ for tree in gbrt.estimators_],
                      axis=0)
         indices = np.argsort(importances)[::-1]
         # print the list of features and assigning number to each
         count = 0
         for i in list(X_train.columns.values):
             print("{} is feature {}".format(i,count))
             count +=1
         print()
         # Print the feature ranking
         print("Feature ranking:")
         for f in range(X_train.shape[1]):
             print("%d. feature %d (%f)" % (f + 1, indices[f], importances[indices[f]]))
```

```
salesVolume is feature 0
indexPrice is feature 1
rate is feature 2
gdp is feature 3
gdpGrowth is feature 4
numberHousehold is feature 5
affordability is feature 6
medianincome is feature 7

Feature ranking:
1. feature 7 (0.487810)
2. feature 1 (0.276482)
3. feature 6 (0.097341)
4. feature 5 (0.075114)
5. feature 3 (0.032181)
6. feature 2 (0.030677)
7. feature 0 (0.000395)
8. feature 4 (0.000000)
```

```
In [25]: print ("R-squared for Train: %.2f" %gbrt.score(X_train, y_train))
         print ("R-squared for Test: %.2f" %gbrt.score(X_test, y_test))
```

```
R-squared for Train: 0.87
R-squared for Test: 0.79
```

Default parameters of GBRT with n_estimators=10 already shown a good score of R-squared in both Train and Test, however, we want to see if we can optimize it more using ShuffleSplit cross-validation and GridSearchCV

- function to find the best parameter

In [26]:
```
def GradientBooster(param_grid, n_jobs):

    estimator = GradientBoostingRegressor()

#Cross-validation using ShuffleSplit which randomly shuffles and selects Train and CV
#There are other methods like the KFold split.
    cv = ShuffleSplit(X_train.shape[0], test_size=0.1)
#Using GridSearchCV to evaluate the classifier
    classifier = GridSearchCV(estimator=estimator, cv=cv, param_grid=param_grid, n_jo

#We'll now fit the training dataset to this classifier
    classifier.fit(X_train, y_train)

#print the result
    print ("Best Estimator learned through GridSearch")
    print()
    print (classifier.best_estimator_)

    return cv, classifier.best_estimator_
```

- function to plot the learning result

In [27]:
```
print(__doc__)


def plot_learning_curve(estimator, title, X, y, ylim=None, cv=None,
                        n_jobs=1, train_sizes=np.linspace(.1, 1.0, 5)):
    """
    Generate a simple plot of the test and traning learning curve.

    Parameters
    ----------
    estimator : object type that implements the "fit" and "predict" methods
        An object of that type which is cloned for each validation.

    title : string
        Title for the chart.

    X : array-like, shape (n_samples, n_features)
        Training vector, where n_samples is the number of samples and
        n_features is the number of features.

    y : array-like, shape (n_samples) or (n_samples, n_features), optional
        Target relative to X for classification or regression;
        None for unsupervised learning.

    ylim : tuple, shape (ymin, ymax), optional
        Defines minimum and maximum yvalues plotted.
```

```
        cv : integer, cross-validation generator, optional
            If an integer is passed, it is the number of folds (defaults to 3).
            Specific cross-validation objects can be passed, see
            sklearn.cross_validation module for the list of possible objects

        n_jobs : integer, optional
            Number of jobs to run in parallel (default 1).
        """
        plt.figure()
        plt.title(title)
        if ylim is not None:
            plt.ylim(*ylim)
        plt.xlabel("Training examples")
        plt.ylabel("Score")
        train_sizes, train_scores, test_scores = learning_curve(
            estimator, X, y, cv=cv, n_jobs=n_jobs, train_sizes=train_sizes)
        train_scores_mean = np.mean(train_scores, axis=1)
        train_scores_std = np.std(train_scores, axis=1)
        test_scores_mean = np.mean(test_scores, axis=1)
        test_scores_std = np.std(test_scores, axis=1)
        plt.grid()

        plt.fill_between(train_sizes, train_scores_mean - train_scores_std,
                         train_scores_mean + train_scores_std, alpha=0.1,
                         color="r")
        plt.fill_between(train_sizes, test_scores_mean - test_scores_std,
                         test_scores_mean + test_scores_std, alpha=0.1, color="g")
        plt.plot(train_sizes, train_scores_mean, 'o-', color="r",
                 label="Training score")
        plt.plot(train_sizes, test_scores_mean, 'o-', color="g",
                 label="Cross-validation score")

        plt.legend(loc="best")
        return plt
```

```
Automatically created module for IPython interactive environment
```

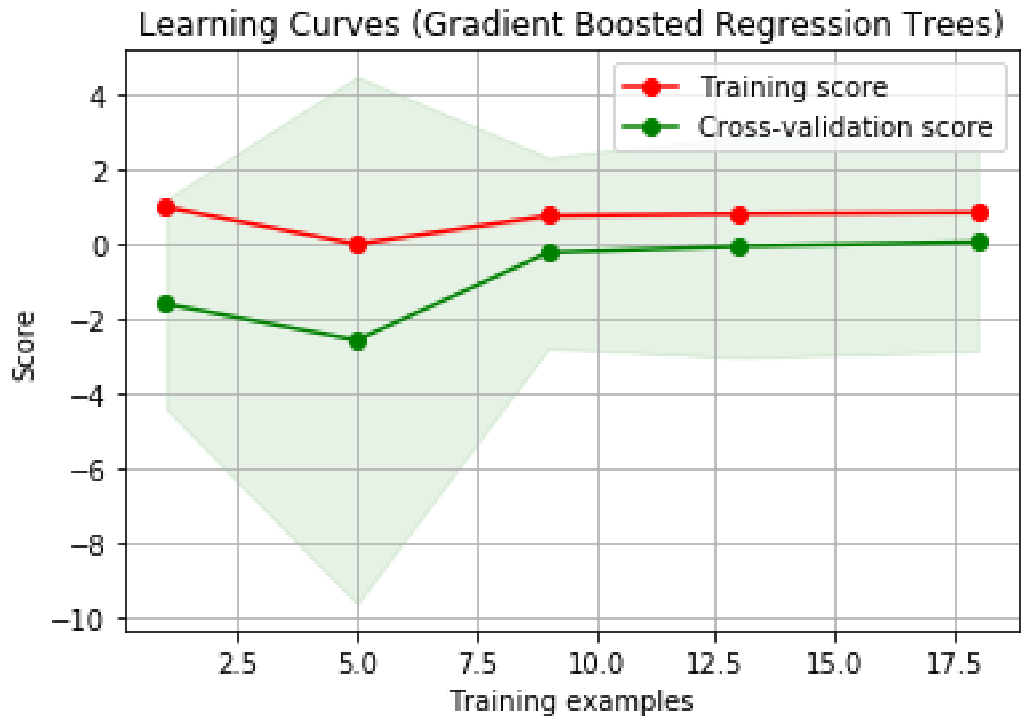
In [28]:
```
param_grid={'n_estimators':[10],
            'learning_rate': [0.1],# 0.05, 0.02, 0.01],
            'max_depth':[6],#4,6],
            'min_samples_leaf':[3],#,5,9,17],
            'max_features':[1.0],#,0.3]#,0.1]
           }
n_jobs=4

# fit GBRT to the digits training dataset by calling the function we just created.
cv,best_est=GradientBooster(param_grid, n_jobs)
```

```
Best Estimator learned through GridSearch

GradientBoostingRegressor(alpha=0.9, criterion='friedman_mse', init=None,
             learning_rate=0.1, loss='ls', max_depth=6, max_features=1.0,
             max_leaf_nodes=None, min_impurity_decrease=0.0,
             min_impurity_split=None, min_samples_leaf=3,
             min_samples_split=2, min_weight_fraction_leaf=0.0,
             n_estimators=10, n_iter_no_change=None, presort='auto',
             random_state=None, subsample=1.0, tol=0.0001,
             validation_fraction=0.1, verbose=0, warm_start=False)
```

In [29]:
```
#so we got back the best estimator parameters based on GridSearch as follows:
print ("Best Estimator Parameters")
print ("---------------------------")
print ("n_estimators: %d" %best_est.n_estimators)
print ("max_depth: %d" %best_est.max_depth)
print ("Learning Rate: %.1f" %best_est.learning_rate)
print ("min_samples_leaf: %d" %best_est.min_samples_leaf)
print ("max_features: %.1f" %best_est.max_features)

print ("Train R-squared: %.2f" %best_est.score(X_train,y_train))

#We believe that each of these parameters is critical for the method to learn better.
#We hope that some of them will help address overfitting issues as well.
```

```
Best Estimator Parameters
---------------------------
n_estimators: 10
max_depth: 6
Learning Rate: 0.1
min_samples_leaf: 3
max_features: 1.0
Train R-squared: 0.87
```

In [30]:
```
#call the plot_learning_curve module by feeding it the estimator

#The module simply runs the estimator multiple times on subsets of the data provided
#We're feeding the best parameters we've learned from GridSearchCV to the estimator n
#We may need to adjust the hyperparameters further if there is overfitting or underfi
title = "Learning Curves (Gradient Boosted Regression Trees)"
estimator = GradientBoostingRegressor(n_estimators=best_est.n_estimators, max_depth=be
                                      learning_rate=best_est.learning_rate, min_sampl
                                      max_features=best_est.max_features)
plot_learning_curve(estimator, title, X_train, y_train, cv=cv, n_jobs=n_jobs)
plt.show()
```

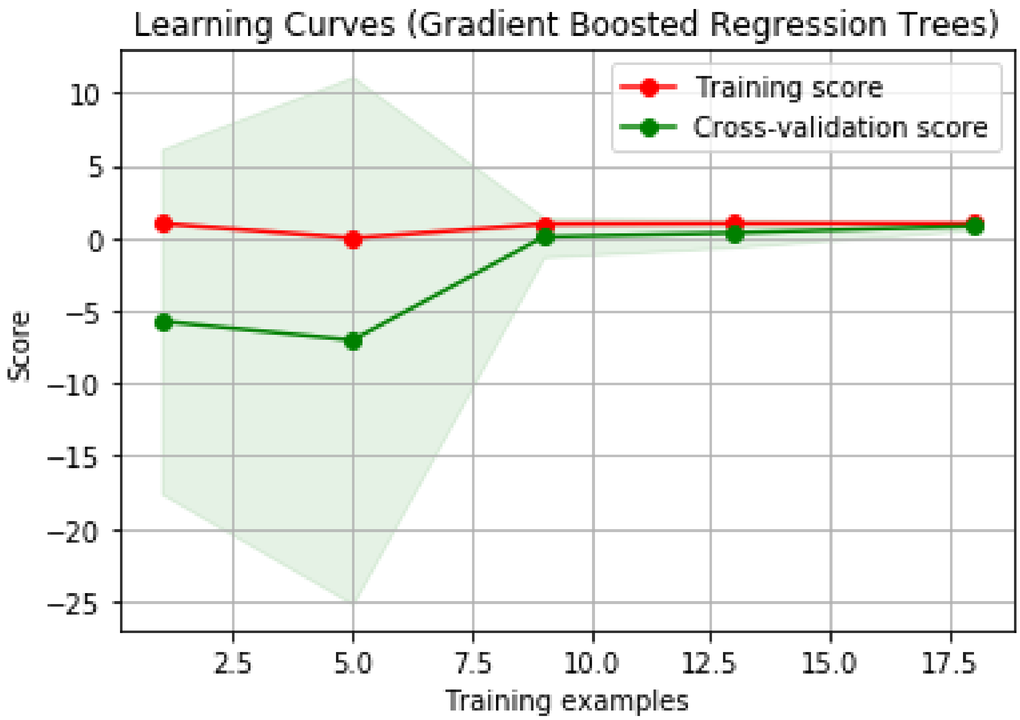



```
In [31]: #Re-fitting to the train set
         estimator.fit(X_train, y_train)

         #Calculating train/test scores - R-squared value
         print ("Train R-squared: %.2f" %estimator.score(X_train, y_train))
         print ("Test R-squared: %.2f" %estimator.score(X_test, y_test))
```

```
Train R-squared: 0.87
Test R-squared: 0.72
```

Looks like we've done an okay job getting about ~0.71 R-squared on the cv set. However, the default result is still better. Therefore, from the learning curve, it seems that we may be able to do a bit better with more estimators.

```
In [32]: #call the plot_learning_curve module by feeding it the estimator again but this time 
         title = "Learning Curves (Gradient Boosted Regression Trees)"
         estimator = GradientBoostingRegressor(n_estimators=100, max_depth=best_est.max_depth,
                                               learning_rate=best_est.learning_rate, min_sampl
                                               max_features=best_est.max_features)
         plot_learning_curve(estimator, title, X_train, y_train, cv=cv, n_jobs=n_jobs)
         plt.show()
```




```
In [33]: #Re-fitting to the train set
         estimator.fit(X_train, y_train)

         #Calculating train/test scores - R-squared value
         print ("Train R-squared: %.2f" %estimator.score(X_train, y_train))
         print ("Test R-squared: %.2f" %estimator.score(X_test, y_test))
```

```
Train R-squared: 1.00
Test R-squared: 0.97
```

It did improve the training score but there's way more overfitting. This possibly could be addressed by further reducing learning rate. However, we might not see a major improvement unless we can obtain more samples.

```
In [34]: #Switching back to the default model
         gbrt=GradientBoostingRegressor(n_estimators=10)
         gbrt.fit(X_train, y_train)
         y_pred=gbrt.predict(X_test)

         #Calculating train/test scores - R-squared value
         print ("Train R-squared: %.2f" %gbrt.score(X_train, y_train))
         print ("Test R-squared: %.2f" %gbrt.score(X_test, y_test))
```

```
Train R-squared: 0.87
Test R-squared: 0.79
```

```
In [35]: print("Prediction Result: ")
         for i in y_pred:
             print (i)

         print()
         print("Actual Result: ")
         y_test.head()
```

```
Prediction Result:
264021.7048683567
237654.1439182278
392462.62231642473

Actual Result:
```

```
Out[35]: year
         2006    251281.1776
         2005    235329.2691
         2017    480240.1579
         Name: price, dtype: float64
```

1.3.1 In conclusion, our final R-squared on the London house price dataset is ~0.79