Problem Statement

In this assignment students will build the random forest model after normalizing the variable to house pricing from boston data set.

Following the code to get data into the environment:

In [16]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn import datasets
boston = datasets.load_boston()
features = pd.DataFrame(boston.data, columns=boston.feature_names)
targets = boston.target
```

In [17]:
```
features.head()
```

Out[17]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT
0	6.32e-03	18.0	2.31	0.0	0.54	6.58	65.2	4.09	1.0	296.0	15.3	396.90	4.98
1	2.73e-02	0.0	7.07	0.0	0.47	6.42	78.9	4.97	2.0	242.0	17.8	396.90	9.14
2	2.73e-02	0.0	7.07	0.0	0.47	7.18	61.1	4.97	2.0	242.0	17.8	392.83	4.03
3	3.24e-02	0.0	2.18	0.0	0.46	7.00	45.8	6.06	3.0	222.0	18.7	394.63	2.94
4	6.91e-02	0.0	2.18	0.0	0.46	7.15	54.2	6.06	3.0	222.0	18.7	396.90	5.33

In [18]:
```
features.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 506 entries, 0 to 505
Data columns (total 13 columns):
CRIM       506 non-null float64
ZN         506 non-null float64
INDUS      506 non-null float64
CHAS       506 non-null float64
NOX        506 non-null float64
RM         506 non-null float64
AGE        506 non-null float64
DIS        506 non-null float64
RAD        506 non-null float64
TAX        506 non-null float64
PTRATIO    506 non-null float64
B          506 non-null float64
LSTAT      506 non-null float64
dtypes: float64(13)
memory usage: 51.5 KB
```

In [19]:
```
features.isnull().sum()
```

Out[19]:
```
CRIM       0
ZN         0
INDUS      0
CHAS       0
NOX        0
RM         0
AGE        0
DIS        0
RAD        0
TAX        0
PTRATIO    0
B          0
LSTAT      0
dtype: int64
```

In [20]:
```
targets.shape
```

Out[20]:
```
(506,)
```

In [21]:
```
# Combining the data
names = ['CRIM','ZN','INDUS','CHAS','NOX','RM','AGE','DIS','RAD','TAX','PTRATIO','B','LSTAT','MEDV']
dataset = pd.DataFrame(data=np.c_[boston['data'], boston['target']], columns=names )
dataset.head()
```

Out[21]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	MEDV
0	6.32e-03	18.0	2.31	0.0	0.54	6.58	65.2	4.09	1.0	296.0	15.3	396.90	4.98	24.0
1	2.73e-02	0.0	7.07	0.0	0.47	6.42	78.9	4.97	2.0	242.0	17.8	396.90	9.14	21.6
2	2.73e-02	0.0	7.07	0.0	0.47	7.18	61.1	4.97	2.0	242.0	17.8	392.83	4.03	34.7
3	3.24e-02	0.0	2.18	0.0	0.46	7.00	45.8	6.06	3.0	222.0	18.7	394.63	2.94	33.4
4	6.91e-02	0.0	2.18	0.0	0.46	7.15	54.2	6.06	3.0	222.0	18.7	396.90	5.33	36.2

In [22]:
```
# descriptions
#pd.set_option('precision', 0)
dataset.describe()
```

Out[22]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	MEDV
count	5.06e+02	506.00	506.00	506.00	506.00	506.00	506.00	506.00	506.00	506.00	506.00	506.00	506.00	506.00
mean	3.59e+00	11.36	11.14	0.07	0.55	6.28	68.57	3.80	9.55	408.24	18.46	356.67	12.65	22.53
std	8.60e+00	23.32	6.86	0.25	0.12	0.70	28.15	2.11	8.71	168.54	2.16	91.29	7.14	9.20
min	6.32e-03	0.00	0.46	0.00	0.39	3.56	2.90	1.13	1.00	187.00	12.60	0.32	1.73	5.00
25%	8.20e-02	0.00	5.19	0.00	0.45	5.89	45.02	2.10	4.00	279.00	17.40	375.38	6.95	17.02
50%	2.57e-01	0.00	9.69	0.00	0.54	6.21	77.50	3.21	5.00	330.00	19.05	391.44	11.36	21.20
75%	3.65e+00	12.50	18.10	0.00	0.62	6.62	94.07	5.19	24.00	666.00	20.20	396.23	16.96	25.00
max	8.90e+01	100.00	27.74	1.00	0.87	8.78	100.00	12.13	24.00	711.00	22.00	396.90	37.97	50.00

In [23]:

```python
# descriptions
pd.set_option('precision', 1)
dataset.describe()
```

Out[23]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	MEDV
count	5.1e+02	506.0	506.0	5.1e+02	506.0	506.0	506.0	506.0	506.0	506.0	506.0	506.0	506.0	506.0
mean	3.6e+00	11.4	11.1	6.9e-02	0.6	6.3	68.6	3.8	9.5	408.2	18.5	356.7	12.7	22.5
std	8.6e+00	23.3	6.9	2.5e-01	0.1	0.7	28.1	2.1	8.7	168.5	2.2	91.3	7.1	9.2
min	6.3e-03	0.0	0.5	0.0e+00	0.4	3.6	2.9	1.1	1.0	187.0	12.6	0.3	1.7	5.0
25%	8.2e-02	0.0	5.2	0.0e+00	0.4	5.9	45.0	2.1	4.0	279.0	17.4	375.4	6.9	17.0
50%	2.6e-01	0.0	9.7	0.0e+00	0.5	6.2	77.5	3.2	5.0	330.0	19.1	391.4	11.4	21.2
75%	3.6e+00	12.5	18.1	0.0e+00	0.6	6.6	94.1	5.2	24.0	666.0	20.2	396.2	17.0	25.0
max	8.9e+01	100.0	27.7	1.0e+00	0.9	8.8	100.0	12.1	24.0	711.0	22.0	396.9	38.0	50.0

In [24]:

```python
# descriptions
pd.set_option('precision', 2)
dataset.describe()
```

Out[24]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	MEDV
count	5.06e+02	506.00	506.00	506.00	506.00	506.00	506.00	506.00	506.00	506.00	506.00	506.00	506.00	506.00
mean	3.59e+00	11.36	11.14	0.07	0.55	6.28	68.57	3.80	9.55	408.24	18.46	356.67	12.65	22.53
std	8.60e+00	23.32	6.86	0.25	0.12	0.70	28.15	2.11	8.71	168.54	2.16	91.29	7.14	9.20
min	6.32e-03	0.00	0.46	0.00	0.39	3.56	2.90	1.13	1.00	187.00	12.60	0.32	1.73	5.00
25%	8.20e-02	0.00	5.19	0.00	0.45	5.89	45.02	2.10	4.00	279.00	17.40	375.38	6.95	17.02
50%	2.57e-01	0.00	9.69	0.00	0.54	6.21	77.50	3.21	5.00	330.00	19.05	391.44	11.36	21.20
75%	3.65e+00	12.50	18.10	0.00	0.62	6.62	94.07	5.19	24.00	666.00	20.20	396.23	16.96	25.00
max	8.90e+01	100.00	27.74	1.00	0.87	8.78	100.00	12.13	24.00	711.00	22.00	396.90	37.97	50.00

In [30]:

```python
#sns.pairplot(dataset)
```

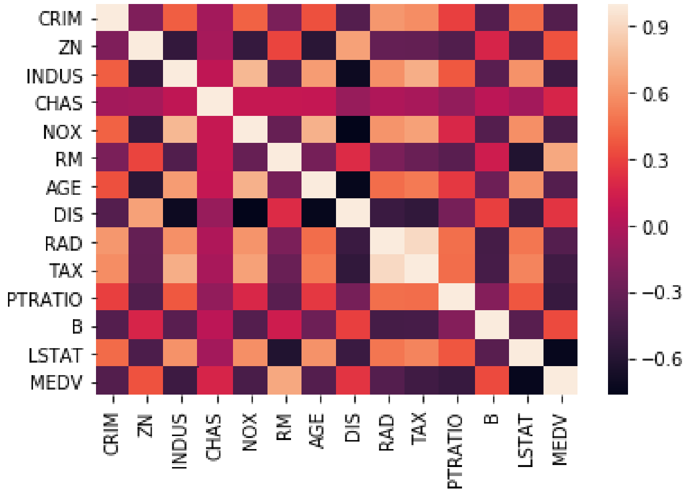
In [26]:
```
corr = dataset.corr()
corr
```

Out[26]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	MEDV
CRIM	1.00	-0.20	0.40	-5.53e-02	0.42	-0.22	0.35	-0.38	6.22e-01	0.58	0.29	-0.38	0.45	-0.39
ZN	-0.20	1.00	-0.53	-4.27e-02	-0.52	0.31	-0.57	0.66	-3.12e-01	-0.31	-0.39	0.18	-0.41	0.36
INDUS	0.40	-0.53	1.00	6.29e-02	0.76	-0.39	0.64	-0.71	5.95e-01	0.72	0.38	-0.36	0.60	-0.48
CHAS	-0.06	-0.04	0.06	1.00e+00	0.09	0.09	0.09	-0.10	-7.37e-03	-0.04	-0.12	0.05	-0.05	0.18
NOX	0.42	-0.52	0.76	9.12e-02	1.00	-0.30	0.73	-0.77	6.11e-01	0.67	0.19	-0.38	0.59	-0.43
RM	-0.22	0.31	-0.39	9.13e-02	-0.30	1.00	-0.24	0.21	-2.10e-01	-0.29	-0.36	0.13	-0.61	0.70
AGE	0.35	-0.57	0.64	8.65e-02	0.73	-0.24	1.00	-0.75	4.56e-01	0.51	0.26	-0.27	0.60	-0.38
DIS	-0.38	0.66	-0.71	-9.92e-02	-0.77	0.21	-0.75	1.00	-4.95e-01	-0.53	-0.23	0.29	-0.50	0.25
RAD	0.62	-0.31	0.60	-7.37e-03	0.61	-0.21	0.46	-0.49	1.00e+00	0.91	0.46	-0.44	0.49	-0.38
TAX	0.58	-0.31	0.72	-3.56e-02	0.67	-0.29	0.51	-0.53	9.10e-01	1.00	0.46	-0.44	0.54	-0.47
PTRATIO	0.29	-0.39	0.38	-1.22e-01	0.19	-0.36	0.26	-0.23	4.65e-01	0.46	1.00	-0.18	0.37	-0.51
B	-0.38	0.18	-0.36	4.88e-02	-0.38	0.13	-0.27	0.29	-4.44e-01	-0.44	-0.18	1.00	-0.37	0.33
LSTAT	0.45	-0.41	0.60	-5.39e-02	0.59	-0.61	0.60	-0.50	4.89e-01	0.54	0.37	-0.37	1.00	-0.74
MEDV	-0.39	0.36	-0.48	1.75e-01	-0.43	0.70	-0.38	0.25	-3.82e-01	-0.47	-0.51	0.33	-0.74	1.00

In [27]:
```
sns.heatmap(corr)
```

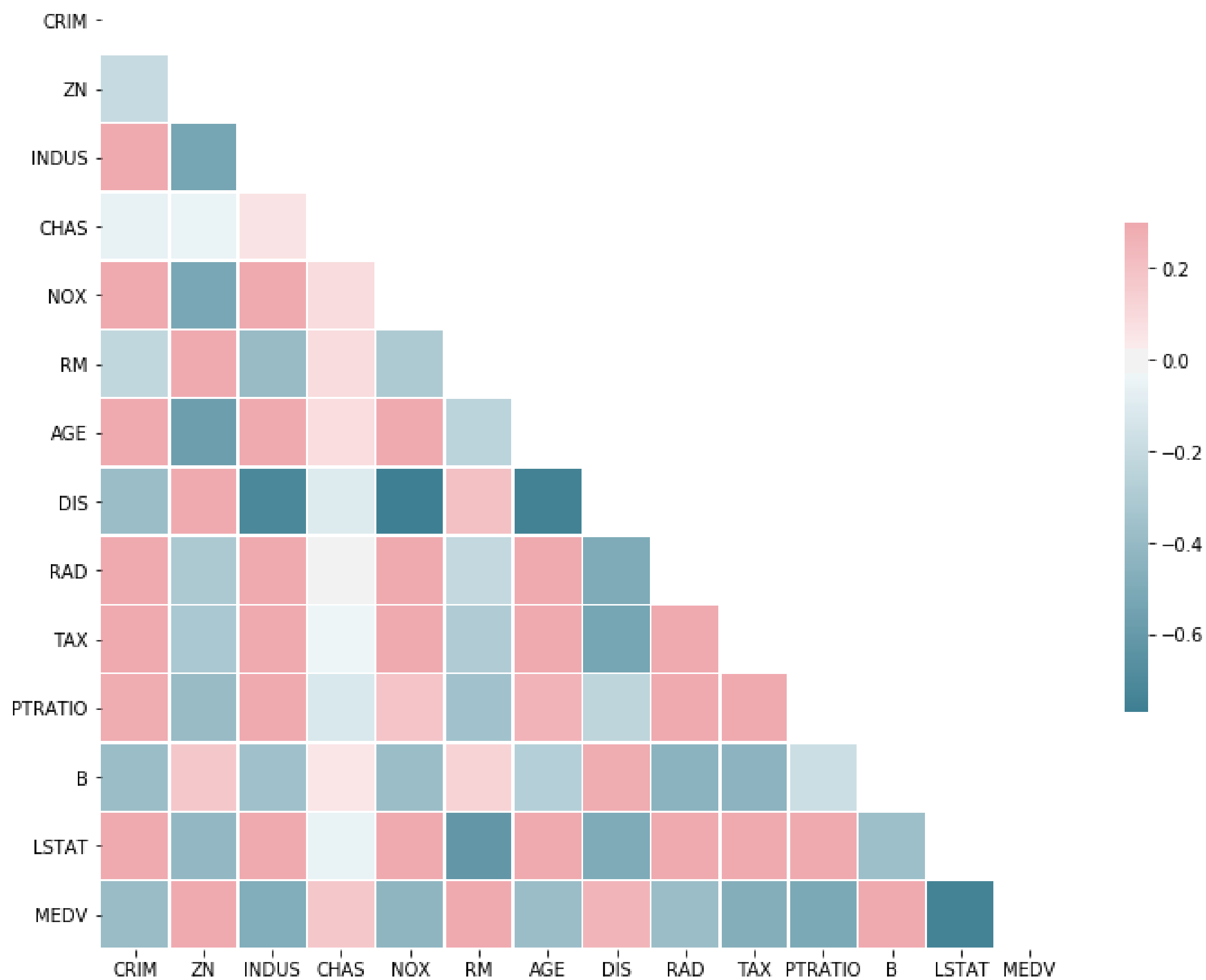
Out[27]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1ab758b23c8>
```



In [ ]:

In [28]:
```
# Generate a mask for the upper triangle
mask = np.zeros_like(corr, dtype=np.bool)
mask[np.triu_indices_from(mask)] = True

# Set up the matplotlib figure
f, ax = plt.subplots(figsize=(12, 10))

# Generate a custom diverging colormap
cmap = sns.diverging_palette(220, 10, as_cmap=True)

# Draw the heatmap with the mask and correct aspect ratio
sns.heatmap(corr, mask=mask, cmap=cmap, vmax=.3, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5})
```

Out[28]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1ab77561f28>
```



CRIM
ZN
INDUS
CHAS
NOX
RM
AGE
DIS
RAD
TAX
PTRATIO
B
LSTAT
MEDV
0.2
0.0
−0.2
−0.4
−0.6

In [29]:
```python
print( boston.DESCR )
```

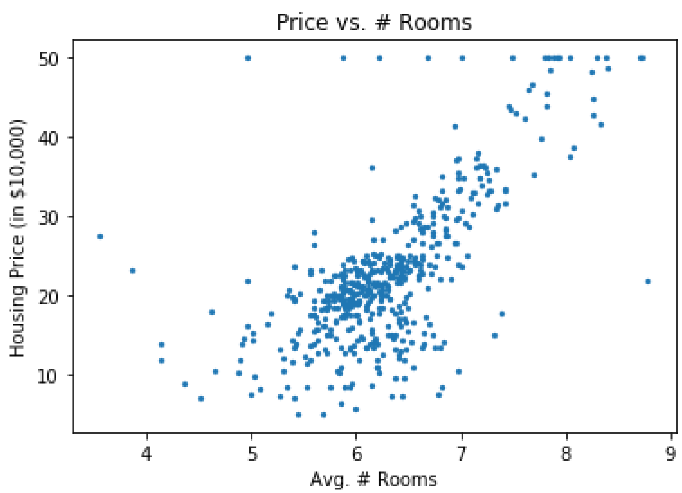
```
Boston House Prices dataset
===========================

Notes
------
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.
http://archive.ics.uci.edu/ml/datasets/Housing (http://archive.ics.uci.edu/ml/datasets/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.

**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 Conferen
ce of Machine Learning, 236-243, University of Massachusetts, Amherst. Morgan Kaufmann.
   - many more! (see http://archive.ics.uci.edu/ml/datasets/Housing) (http://archive.ics.uci.edu/ml/datasets/Housing))
```

In [35]:

```python
# Drawing the chart between Price vs average no of rooms.
import matplotlib.pyplot as plt
%matplotlib inline
plt.scatter( dataset['RM'], dataset['MEDV'], s=5 )
plt.xlabel( "Avg. # Rooms" )
plt.ylabel( "Housing Price (in $10,000)" )
plt.title( "Price vs. # Rooms")
```

Out[35]: Text(0.5,1,'Price vs. # Rooms')



This shows that increase in average no of rooms increase the price also

In [42]:
```
# Drawing the chart between Price vs average no of rooms.
import matplotlib.pyplot as plt
%matplotlib inline
plt.scatter( dataset['LSTAT'], dataset['MEDV'], s=5)
plt.xlabel( "Lower Status. # Population" )
plt.ylabel( "Housing Price (in $10,000)" )
plt.title( "Price vs. # Lower Status")
```

Out[42]:
```
Text(0.5,1,'Price vs. # Lower Status')
```

More is the Lower Status of Populaton, lesser is the price

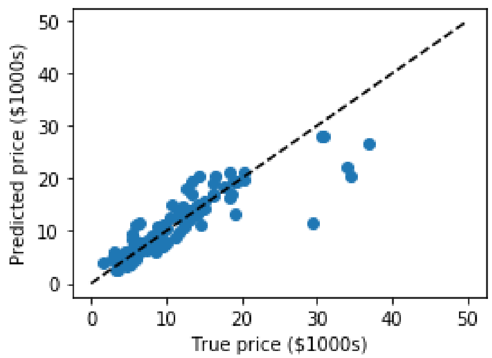
We are not plotting graph for others as its value are not co-related to the Price Negatively or Positively

Data Preprocessing

Splitting the data

In [61]:
```
X = dataset.drop('LSTAT', axis=1)
y = dataset['LSTAT']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 10)
```

In [62]:
```
from sklearn.ensemble import GradientBoostingRegressor

clf = GradientBoostingRegressor()
clf.fit(X_train, y_train)

y_train_pred = clf.predict(X_train)

predicted = clf.predict(X_test)
y_test_pred = predicted
expected = y_test

plt.figure(figsize=(4, 3))
plt.scatter(expected, predicted)
plt.plot([0, 50], [0, 50], '--k')
plt.axis('tight')
plt.xlabel('True price ($1000s)')
plt.ylabel('Predicted price ($1000s)')
plt.tight_layout()
```



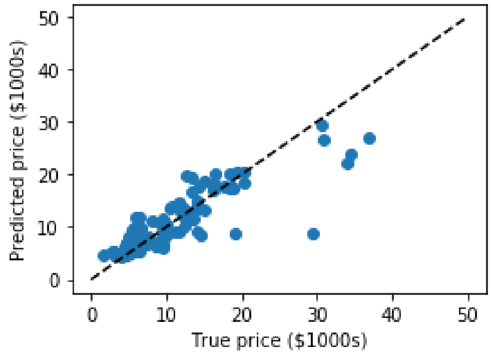
In [64]:

```
import math
from math import sqrt
# Importing Regression Metrics - Performance Evaluation
from sklearn.metrics import mean_squared_error
from sklearn.metrics import r2_score

print('GradientBoostingRegressor -', 'RMSE Train:', math.sqrt(mean_squared_error(y_train_pred, y_train)))
print('GradientBoostingRegressor -', 'RMSE Test:' ,math.sqrt(mean_squared_error(y_test_pred, y_test)))
print('GradientBoostingRegressor -', 'R2_score Train:', r2_score(y_train_pred, y_train))
print('GradientBoostingRegressor -', 'R2_score Test:' ,r2_score(y_test_pred, y_test))
```

```
GradientBoostingRegressor - RMSE Train: 1.6537539141392041
GradientBoostingRegressor - RMSE Test: 3.454942596221226
GradientBoostingRegressor - R2_score Train: 0.9372409354164829
GradientBoostingRegressor - R2_score Test: 0.6568459385504346
```

In [65]:

```
'''from sklearn.ensemble import RandomForestRegressor
    from sklearn.cross_validation import cross_val_score, ShuffleSplit

    boston = load_boston()
    X = boston["data"]
    Y = boston["target"]
    names = boston["feature_names"]

    rf = RandomForestRegressor(n_estimators=20, max_depth=4)
    scores = []
    for i in range(X.shape[1]):
        score = cross_val_score(rf, X[:, i:i + 1],
                                Y, scoring="r2", cv=ShuffleSplit(len(X), 3, .3))
        scores.append((round(np.mean(score), 3), names[i]))

    print sorted(scores, reverse=True)
 '''
from sklearn.ensemble import RandomForestRegressor

clf = RandomForestRegressor(n_estimators=20, max_depth=4)
clf.fit(X_train, y_train)

y_train_pred = clf.predict(X_train)

predicted = clf.predict(X_test)
y_test_pred = predicted
expected = y_test

plt.figure(figsize=(4, 3))
plt.scatter(expected, predicted)
plt.plot([0, 50], [0, 50], '--k')
plt.axis('tight')
plt.xlabel('True price ($1000s)')
plt.ylabel('Predicted price ($1000s)')
plt.tight_layout()
```



In [66]:
```
print('Random Forest Regresson -', 'RMSE Train:', math.sqrt(mean_squared_error(y_train_pred, y_train)))
print('Random Forest Regresson -', 'RMSE Test:' ,math.sqrt(mean_squared_error(y_test_pred, y_test)))
print('Random Forest Regresson -', 'R2_score Train:', r2_score(y_train_pred, y_train))
print('Random Forest Regresson -', 'R2_score Test:' ,r2_score(y_test_pred, y_test))
```

```
Random Forest Regresson - RMSE Train: 2.6275844186846284
Random Forest Regresson - RMSE Test: 3.7783922769719287
Random Forest Regresson - R2_score Train: 0.8164160478334849
Random Forest Regresson - R2_score Test: 0.5632285769990709
```

In [ ]: