Fire up libraries

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In [1]:

```
import matplotlib
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
from sklearn import linear_model
```

Load some house sales data

Dataset is from house sales in King County, the region where the city of Seattle, WA is located.

In [2]:

```
sales = pd.read_csv('home_data.csv')
```

In [3]:

```
sales.head()
```

Out[3]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot
0	7129300520	20141013T000000	221900	3	1.00	1180	5650
1	6414100192	20141209T000000	538000	3	2.25	2570	7242
2	5631500400	20150225T000000	180000	2	1.00	770	10000
3	2487200875	20141209T000000	604000	4	3.00	1960	5000
4	1954400510	20150218T000000	510000	3	2.00	1680	8080

5 rows × 21 columns

In [4]:

```
sales[sales['id']==1839920160]
```

Out[4]:

	id	date	price	bedrooms	bathrooms	sqft_living	sq
11860	1839920160	20140714T000000	432000	3	2.0	1870	70

1 rows × 21 columns

In [5]:

```
sales.keys()
```

Out[5]:

```
Index(['id', 'date', 'price', 'bedrooms', 'bathrooms', 'sqft_living',
       'sqft_lot', 'floors', 'waterfront', 'view', 'condition', 'grade',
       'sqft_above', 'sqft_basement', 'yr_built', 'yr_renovated', 'zipcod
e',
       'lat', 'long', 'sqft_living15', 'sqft_lot15'],
      dtype='object')
```

In [6]:

```
sales.shape
```

Out[6]:

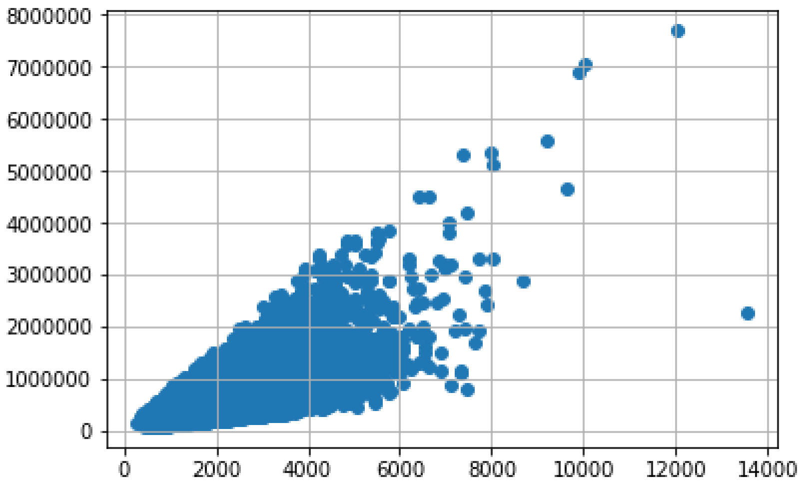
```
(21613, 21)
```

Exploring the data for housing sales

The house price is correlated with the number of square feet of living space.

In [7]:

```
plt.grid('on')
plt.scatter(sales['sqft_living'], sales['price'])
plt.show()
```



Create a simple regression model of sqft_living to price

Split data into training and testing.
We use random_state=200 so that everyone running this notebook gets the same results. In practice, you may set a random seed.

In [8]:

```
train_data = sales.sample(frac=0.8, random_state=200)
test_data  = sales.drop(train_data.index)
print(train_data.shape, test_data.shape)
```

```
(17290, 21) (4323, 21)
```

In [9]:

```
train_data.head()
```

Out[9]:

	id	date	price	bedrooms	bathrooms	sqft_living	sq1
11860	1839920160	20140714T000000	432000	3	2.00	1870	708
12446	6705850140	20141009T000000	750000	4	2.75	3170	763
10556	924069190	20140819T000000	440000	3	1.75	2000	118
4828	3211270170	20140523T000000	404000	4	3.00	4060	356
3502	9523103001	20141013T000000	389000	2	1.00	850	327

5 rows × 21 columns

In [10]:

```
test_data.head()
```

Out[10]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_
3	2487200875	20141209T000000	604000	4	3.0	1960	5000
4	1954400510	20150218T000000	510000	3	2.0	1680	8080
5	7237550310	20140512T000000	1225000	4	4.5	5420	1019
17	6865200140	20140529T000000	485000	4	1.0	1600	4300
18	16000397	20141205T000000	189000	2	1.0	1200	9850

5 rows × 21 columns

Build the regression model using only sqft_living as a feature

In [11]:

```
x_train = train_data['sqft_living'].values.reshape(-1,1)
y_train = train_data['price'].values.reshape(-1,1)
```

In [12]:

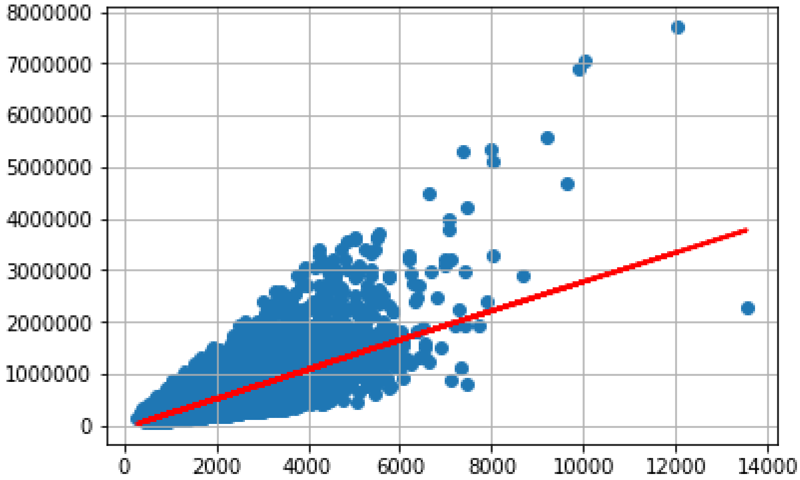
```
simple_model = linear_model.LinearRegression()
simple_model.fit(x_train, y_train)
```

Out[12]:

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normalize=Fals
e)
```

In [13]:

```
plt.grid('on')
plt.scatter(x_train, y_train)
plt.plot(x_train, simple_model.predict(x_train), color='red', linewidth=2)
plt.show()
```



Let's show what our predictions look like

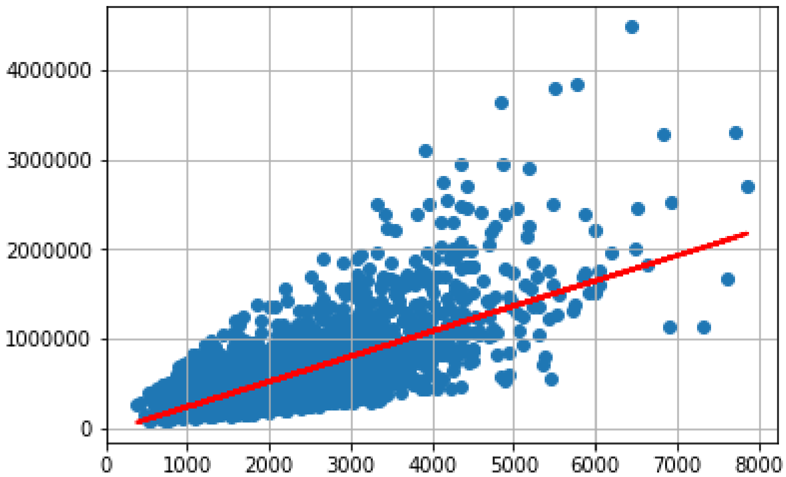
In [14]:

```
x_test = test_data['sqft_living'].values.reshape(-1,1)
y_test = test_data['price'].values.reshape(-1,1)

y_pred = simple_model.predict(x_test)
```

In [15]:

```
plt.grid('on')
plt.scatter(x_test, y_test)
plt.plot(x_test,y_pred, color='red', linewidth=2)
plt.show()
```



Evaluate the simple model

In [16]:

```
def rmse(predictions, targets):
    return np.sqrt(((predictions - targets) ** 2).mean())
```

In [17]:

```
print('intercept:', simple_model.intercept_, 'coefficients:', simple_model.coef_)
# The mean squared error
print("RMSE: %.2f" % (rmse(y_pred, y_test)))
```

```
intercept: [-46493.04519733] coefficients: [[ 282.27187583]]
RMSE: 254323.39
```

RMSE of about $254.323,39

Explore other features in the data

To build a more elaborate model, we will explore using more features.

In [18]:

```
my_features = ['bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors', 'zipcode']
```

In [19]:

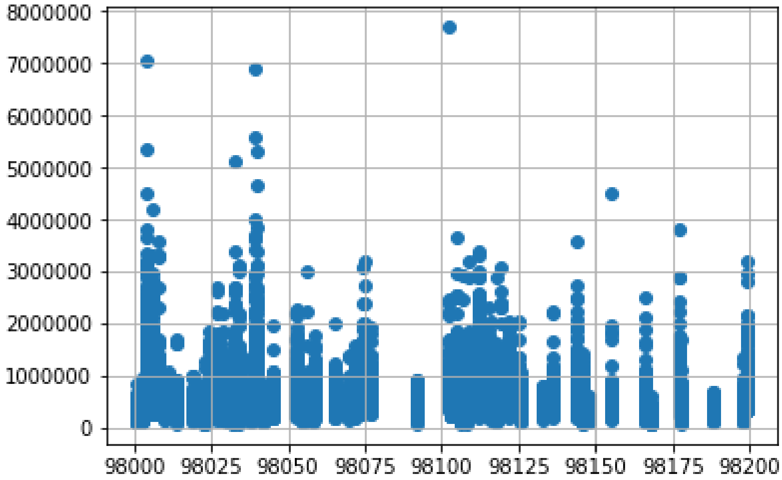
```
sales[my_features].describe()
```

Out[19]:

	bedrooms	bathrooms	sqft_living	sqft_lot	floors	
count	21613.000000	21613.000000	21613.000000	2.161300e+04	21613.000000	2161
mean	3.370842	2.114757	2079.899736	1.510697e+04	1.494309	9807
std	0.930062	0.770163	918.440897	4.142051e+04	0.539989	53.50
min	0.000000	0.000000	290.000000	5.200000e+02	1.000000	9800
25%	3.000000	1.750000	1427.000000	5.040000e+03	1.000000	9803
50%	3.000000	2.250000	1910.000000	7.618000e+03	1.500000	9806
75%	4.000000	2.500000	2550.000000	1.068800e+04	2.000000	9811
max	33.000000	8.000000	13540.000000	1.651359e+06	3.500000	9819

In [20]:

```
#sales.show(view='BoxWhisker Plot', x='zipcode', y='price')
plt.grid('on')
plt.scatter(sales['zipcode'], sales['price'])
plt.show()
```



98039 is the most expensive zip code.

Build a regression model with more features

In [21]:

```
#my_features_model = (train_data,target='price',features=my_features,validation_set=Non
e)
x_train = train_data[my_features].values.reshape(-1,len(my_features))
y_train = train_data['price'].values.reshape(-1,1)
```

In [22]:

```
mult_model = linear_model.LinearRegression()
mult_model.fit(x_train, y_train)
```

Out[22]:

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normalize=Fals
e)
```

Comparing the results of the simple model with adding more features

In [23]:

```
x_test = test_data[my_features].values.reshape(-1,len(my_features))
y_test = test_data['price'].values.reshape(-1,1)

y_pred = mult_model.predict(x_test)
```

In [24]:

```
print('intercept:', mult_model.intercept_, 'coefficients:', mult_model.coef_)
# The mean squared error
print("RMSE: %.2f" % (rmse(y_pred, y_test)))
```

```
intercept: [-56348418.94956037] coefficients: [[ -6.17445455e+04   1.88053
371e+04   3.17237961e+02  -2.88006880e-01
   -9.68870610e+03   5.75218487e+02]]
RMSE: 249311.90
```

The RMSE goes down from $254.323,39 to $228.024,43 with more features.

Apply learned models to predict prices of 3 houses

The first house we will use is considered an "average" house in Seattle.

In [25]:

```
house1 = sales[sales['id']==5309101200]
```

In [26]:

```
house1
```

Out[26]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_
1054	5309101200	20140605T000000	620000	4	2.25	2400	535(

1 rows × 21 columns

In [27]:

```
print (house1['price'])
```

```
1054    620000
Name: price, dtype: int64
```

In [28]:

```
house1['sqft_living']
```

Out[28]:

```
1054    2400
Name: sqft_living, dtype: int64
```

In [29]:

```
print (simple_model.predict(house1['sqft_living'].values.reshape(-1,1)))
```

```
[[ 630959.4568039]]
```

In [30]:

```
print (mult_model.predict(house1[my_features]))
```

```
[[ 630924.33807747]]
```

In this case, the model with more features provides a worse prediction than the simpler model with only 1 feature. However, on average, the model with more features is better.

Prediction for a second, fancier house

We will now examine the predictions for a fancier house.

In [31]:

```
house2 = sales[sales['id']==1925069082]
```

In [32]:

```
house2
```

Out[32]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqf
1361	1925069082	20150511T000000	2200000	5	4.25	4640	227

1 rows × 21 columns

In [33]:

```
print (house2['price'])
```

```
1361    2200000
Name: price, dtype: int64
```

In [34]:

```
print (simple_model.predict(house2['sqft_living'].values.reshape(-1,1)))
```

```
[[ 1263248.45867172]]
```

In [35]:

```
print (mult_model.predict(house2[my_features]))
```

```
[[ 1270172.16078082]]
```

In this case, the model with more features provides a better prediction. This behavior is expected here, because this house is more differentiated by features that go beyond its square feet of living space, especially the fact that it's a waterfront house.

Last house, super fancy

Our last house is a very large one owned by a famous Seattleite.

In [36]:

```
bill_gates = {'bedrooms':[8],
              'bathrooms':[25],
              'sqft_living':[50000],
              'sqft_lot':[225000],
              'floors':[4],
              'zipcode':['98039'],
              'condition':[10],
              'grade':[10],
              'waterfront':[1],
              'view':[4],
              'sqft_above':[37500],
              'sqft_basement':[12500],
              'yr_built':[1994],
              'yr_renovated':[2010],
              'lat':[47.627606],
              'long':[-122.242054],
              'sqft_living15':[5000],
              'sqft_lot15':[40000]}
```

In [37]:

```
print (simple_model.predict(pd.DataFrame(bill_gates)
['sqft_living'].values.reshape(-1,1)))
```

```
[[ 14067100.74649498]]
```

The model predicts a price of over $14M for this house! But we expect the house to cost much more. (There are very few samples in the dataset of houses that are this fancy, so we don't expect the model to capture a perfect prediction here.)

In [38]:

```
print (mult_model.predict(pd.DataFrame(bill_gates)[my_features]))
```

```
[[ 15779944.98847018]]
```

Answers

1 - Selection and summary statistics

In [39]:

```
zip_code = sales[sales['zipcode']==98039]
```

In [40]:

```
my_features = ['price','bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors', 'z
ipcode']
```

In [41]:

```
zip_code[my_features].describe()
```

Out[41]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	zi
count	5.000000e+01	50.000000	50.000000	50.0000	50.000000	50.000000	50
mean	2.160607e+06	4.060000	3.200000	3800.9000	17403.560000	1.560000	98
std	1.166477e+06	0.890081	1.366509	1764.5025	6655.224175	0.501427	0.(
min	7.875000e+05	2.000000	1.000000	1220.0000	6572.000000	1.000000	98
25%	1.401000e+06	4.000000	2.250000	2680.0000	13797.500000	1.000000	98
50%	1.892500e+06	4.000000	3.000000	3560.0000	17188.500000	2.000000	98
75%	2.556250e+06	4.750000	3.687500	4452.5000	20052.250000	2.000000	98
max	6.885000e+06	7.000000	7.750000	9890.0000	35069.000000	2.000000	98

In [42]:

```
print ('O preço médio de venda da vizinhança é $%.2f.' % (zip_code['price'].mean()))
```

```
O preço médio de venda da vizinhança é $2160606.60.
```

2 - Filtering data

In [43]:

```
area_filter = sales[(sales['sqft_living']>=2000) & (sales['sqft_living']<=4000)]
```

In [44]:

```
print(area_filter.head())
```

```
            id             date    price  bedrooms  bathrooms  sqft_living
  \
1   6414100192  20141209T000000   538000         3       2.25         2570

10  1736800520  20150403T000000   662500         3       2.50         3560

15  9297300055  20150124T000000   650000         4       3.00         2950

21  2524049179  20140826T000000  2000000         3       2.75         3050

22  7137970340  20140703T000000   285000         5       2.50         2270


    sqft_lot  floors  waterfront  view     ...      grade  sqft_above  \
1       7242     2.0           0     0     ...          7        2170
10      9796     1.0           0     0     ...          8        1860
15      5000     2.0           0     3     ...          9        1980
21     44867     1.0           0     4     ...          9        2330
22      6300     2.0           0     0     ...          8        2270

    sqft_basement  yr_built  yr_renovated  zipcode      lat     long  \
1             400      1951          1991    98125  47.7210 -122.319
10           1700      1965             0    98007  47.6007 -122.145
15            970      1979             0    98126  47.5714 -122.375
21            720      1968             0    98040  47.5316 -122.233
22              0      1995             0    98092  47.3266 -122.169

    sqft_living15  sqft_lot15
1            1690        7639
10           2210        8925
15           2140        4000
21           4110       20336
22           2240        7005

[5 rows x 21 columns]
```

In [45]:

```
print ('O percentual de casas que possuem áreas entre 2000 e 4000 pés quadrados é de:
%.2f.' % (float(area_filter['zipcode'].count())/(sales['zipcode'].count()) * 100))
```

```
O percentual de casas que possuem áreas entre 2000 e 4000 pés quadrados é
 de: 42.66.
```

3 - Building a regression model with several more features

In [46]:

```
advanced_features = ['bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors', 'zip
code', 'condition', 'grade',
                     'waterfront', 'view', 'sqft_above', 'sqft_basement', 'yr_built']
```