In [157]:
```
import sklearn, pandas
```

Load some house sales data

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

In [84]:
```
sales = pandas.read_csv("c:/Users/thangnd/Desktop/home_data.csv")
```

In [85]:
```
sales.shape
```

Out[85]:
```
(21613, 21)
```

In [88]:
```
sales.head()
```

Out[88]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft_above	sq
0	7129300520	20141013T000000	221900	3	1.00	1180	5650	1.0	0	0	...	7	1180	
1	6414100192	20141209T000000	538000	3	2.25	2570	7242	2.0	0	0	...	7	2170	
2	5631500400	20150225T000000	180000	2	1.00	770	10000	1.0	0	0	...	6	770	
3	2487200875	20141209T000000	604000	4	3.00	1960	5000	1.0	0	0	...	7	1050	
4	1954400510	20150218T000000	510000	3	2.00	1680	8080	1.0	0	0	...	8	1680	

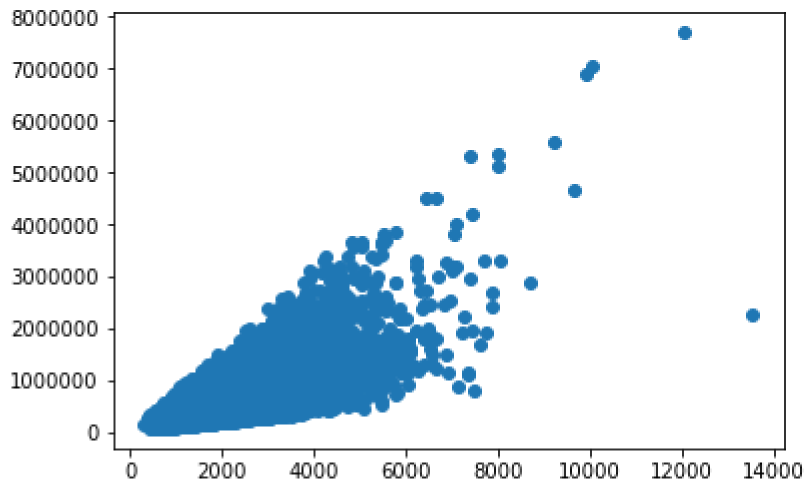
5 rows × 21 columns

Exploring the data for housing sales

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

In [89]:
```
import matplotlib.pyplot as plt
%matplotlib inline
plt.scatter(x=sales["sqft_living"],y=sales["price"])
```

Out[89]:
```
<matplotlib.collections.PathCollection at 0x2431f7b8>
```



Create a simple regression model of sqft_living to price

Split data into training and testing.
We use seed=0 so that everyone running this notebook gets the same results. In practice, you may set a random seed (or let GraphLab Create pick a random seed for you).

In [90]:
```
from sklearn.model_selection import train_test_split
train_data,test_data = train_test_split(sales,train_size=0.8,test_size=0.2, random_state=0)

#x,y: là dataframe sales
```

Build the regression model using only sqft_living as a feature

In [91]:
```python
train_data.head(2)
```

Out[91]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft_above
5268	5100402668	20150218T000000	495000	3	1.0	1570	5510	1.0	0	0	...	7	1070
16909	7856560480	20140808T000000	635000	3	2.5	1780	11000	1.0	0	0	...	8	1210

2 rows × 21 columns

In [127]:
```python
train_data['price'].head()
```

Out[127]:
```
5268     495000
16909    635000
16123    382500
12181    382500
12617    670000
Name: price, dtype: int64
```

In [92]:
```python
from sklearn.linear_model import LinearRegression
import numpy as np
sqft_model = LinearRegression()
sqft_model.fit(np.reshape(train_data["sqft_living"].values, [-1, 1]),train_data["price"])

#x_train: sqft_living, y_train: price
```

Out[92]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
         normalize=False)
```

Evaluate the simple model

In [93]:
```python
print(test_data['price'].mean())
```

```
529242.610687
```

Mean Square Error(MSE)

In [94]:
```
print(mean_squared_error(test_data['price'], sqft_model.predict(np.reshape(test_data["sqft_living"].values, [-1,
```

```
61940787221.49824
```

Root Mean Square Error(RMSE)

In [130]:
```
# Du bao price(y) dua vao x (test_data['sqft_living'])
prediction = sqft_model.predict(np.reshape(test_data["sqft_living"].values, [-1, 1]))
labels = test_data['price']

print(np.sqrt(sklearn.metrics.mean_squared_error(labels.values, prediction)))
```

```
248879.06143647005
```

RMSE of about $248,879$!

In [129]:
```
prediction
```

Out[129]:
```
array([ 357817.97358056, 1277876.09945262,  360657.65915424, ...,
        337940.17456481,  221513.06604396,  417451.37062783])
```

Let's show what our predictions look like

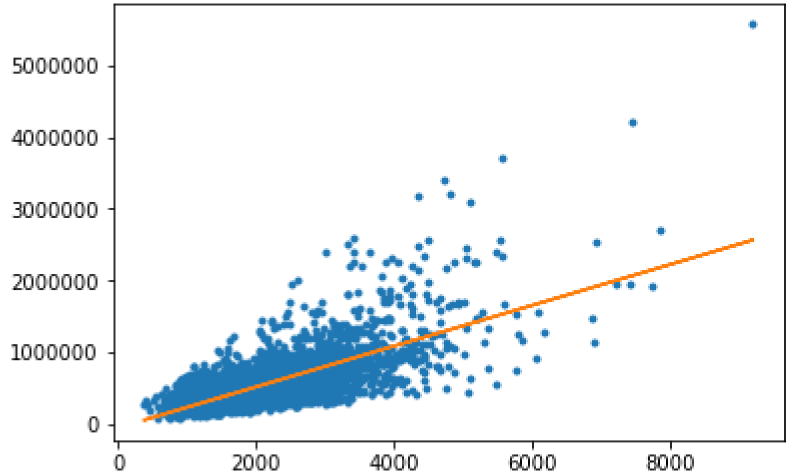
Matplotlib is a Python plotting library that is also useful for plotting. You can install it with:

'pip install matplotlib'

In [96]:
```
import matplotlib.pyplot as plt
%matplotlib inline
```

In [97]:
```
plt.plot(test_data['sqft_living'],
         test_data['price'],'.',
         test_data['sqft_living'],
         sqft_model.predict(np.reshape(test_data["sqft_living"].values, [-1, 1])),
         '-')
```

Out[97]:
```
[<matplotlib.lines.Line2D at 0x240e5780>,
 <matplotlib.lines.Line2D at 0x240e5828>]
```



Above: blue dots are original data, orange line is the prediction from the simple regression.

Below: we can view the learned regression coefficients.

In [132]:
```
#Do chỉ có 01 biến x là sqft_living (X) chỉ có 01 coefficients
sqft_model.coef_
```

Out[132]:
```
array([283.96855737])
```

Below: we can view the learned regression intercept.

In [99]:
```
sqft_model.intercept_
```

Out[99]:
```
-48257.06345556176
```

Explore other features in the data

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

In [100]:
```
my_features = ['bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors', 'zipcode']
```

To build a more elaborate model advance features

In [148]:
```
advanced_features =  ['bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors', 'zipcode','condition','grade
```

In [124]:
```
sales[my_features].head()
```

Out[124]:

	bedrooms	bathrooms	sqft_living	sqft_lot	floors	zipcode
0	3	1.00	1180	5650	1.0	98178
1	3	2.25	2570	7242	2.0	98125
2	2	1.00	770	10000	1.0	98028
3	4	3.00	1960	5000	1.0	98136
4	3	2.00	1680	8080	1.0	98074

In [150]:
```
sales[advanced_features].head()
```

Out[150]:

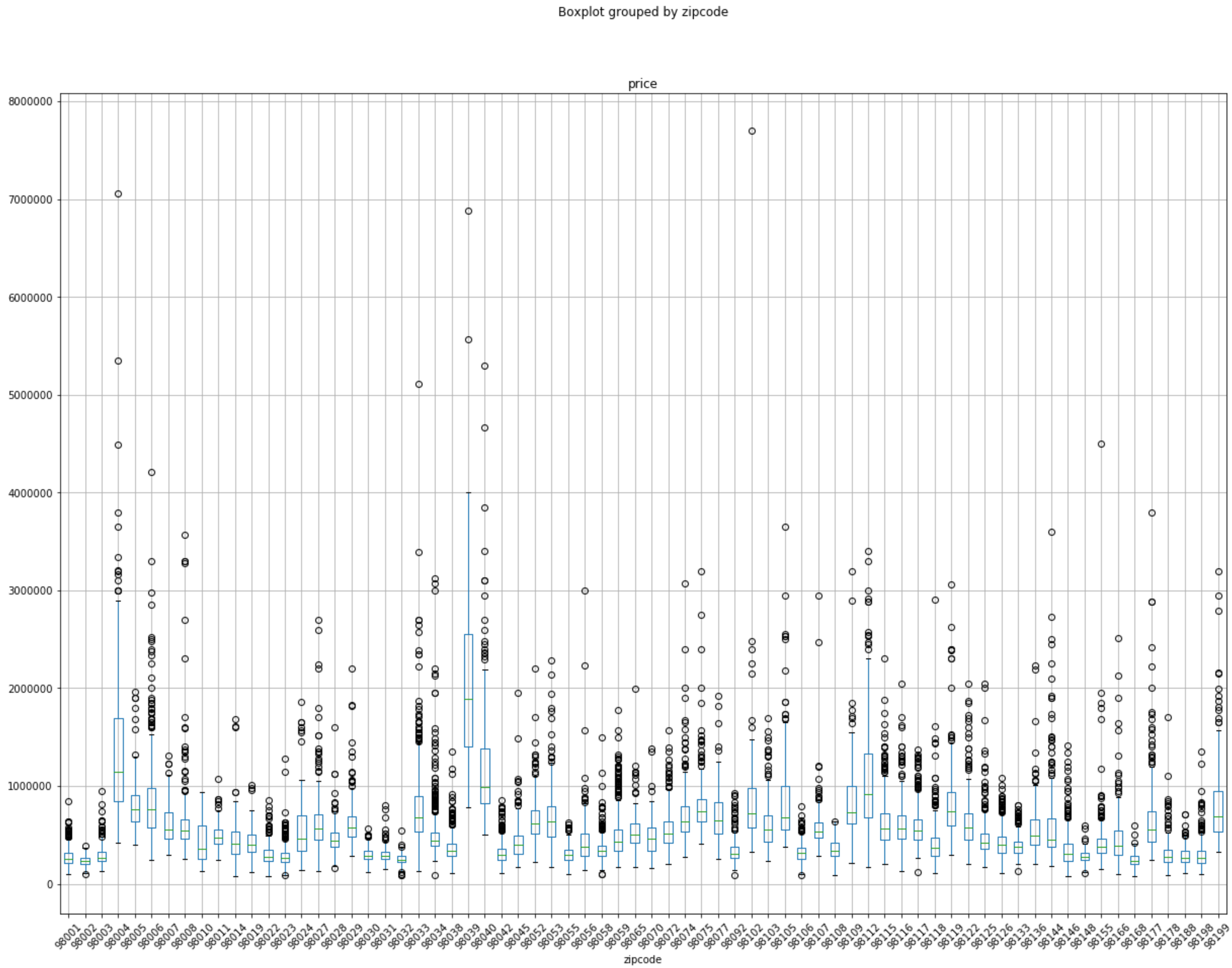
	bedrooms	bathrooms	sqft_living	sqft_lot	floors	zipcode	condition	grade	waterfront	view	sqft_above	sqft_basement	yr_built	y
0	3	1.00	1180	5650	1.0	98178	3	7	0	0	1180	0	1955	
1	3	2.25	2570	7242	2.0	98125	3	7	0	0	2170	400	1951	
2	2	1.00	770	10000	1.0	98028	3	6	0	0	770	0	1933	
3	4	3.00	1960	5000	1.0	98136	5	7	0	0	1050	910	1965	
4	3	2.00	1680	8080	1.0	98074	3	8	0	0	1680	0	1987	

Question 1. With zip code and the highest average home price we found. Choose the average house price of that zip code? (Selection and summary statistics)

Đáp án nhìn vào biểu đồ boxplot có thể thấy với zip code = 98039 thì price cao nhất

In [102]:

```python
#data = sales[["zipcode","price"]].values
ax = sales.boxplot(column="price", by="zipcode", rot=45, figsize=(20, 15))
```



Pull the bar at the bottom to view more of the data.

98039 is the most expensive zip code.

Build a regression model with more features

In [152]:
```
from sklearn.linear_model import LinearRegression
import numpy as np
my_features_model = LinearRegression()
my_features_model.fit(train_data[my_features].values,train_data["price"])
```

Out[152]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
         normalize=False)
```

Build a regression model with advance features

In [153]:
```
from sklearn.linear_model import LinearRegression
import numpy as np
advanced_features_model = LinearRegression()
advanced_features_model.fit(train_data[advanced_features].values,train_data["price"])
```

Out[153]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
         normalize=False)
```

In [104]:
```
print(my_features)
```

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

In [154]:
```
print(advanced_features)
```

```
['bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors', 'zipcode', 'condition', 'grade', 'waterfront',
'view', 'sqft_above', 'sqft_basement', 'yr_built', 'yr_renovated', 'lat', 'long', 'sqft_living15', 'sqft_lot1
5']
```

In [134]:
```
# Với mô hình linear regresstion phải tối thiểu có 2 dimentions trở lên
test_data[my_features].ndim
```

Out[134]:
```
2
```

Comparing the results of the simple model with adding more features

Root Mean Square Error(RMSE) for x = sqft_living

In [106]:
```
labels = test_data['price']

prediction = sqft_model.predict(np.reshape(test_data["sqft_living"].values, [-1, 1]))
print(np.sqrt(sklearn.metrics.mean_squared_error(labels.values, prediction)))
```

```
248879.06143647005
```

Root Mean Square Error(RMSE) for x1,x2,x2,x4,x5,x6 with my_features

In [107]:
```
prediction_features = my_features_model.predict(test_data[my_features].values)
print(np.sqrt(sklearn.metrics.mean_squared_error(labels.values, prediction_features)))
```

```
244004.77443104092
```

Root Mean Square Error(RMSE) for x1,x2,x2,x4,x5,x6 with advanced_features

In [156]:
```
prediction_advance = advanced_features_model.predict(test_data[advanced_features].values)
print(np.sqrt(sklearn.metrics.mean_squared_error(labels.values, prediction_advance)))
```

```
190473.37570966638
```

Question 3. Between the one trained with advanced_features and the model trained with my_features in RMSE. What is the difference? ?(Building a regression model with several more features)

= 244004.77443104092 - 190473.37570966638 = 53531.398721374

Mean Square Error(MSE)

In [135]:
```
print(sklearn.metrics.mean_squared_error(labels.values, prediction_features))
```

```
59538329945.14316
```

we can view the learned regression coefficients. Chúng ta có thể thấy với mỗi features sẽ là một biến tương đương với, trong bài này là 6 tương đương với 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors', 'zipcode')

In [108]:
```
my_features_model.coef_
```

Out[108]:
```
array([-5.66006330e+04,  1.10870936e+04,  3.20408369e+02, -2.89499140e-01,
       -2.41800491e+03,  6.17971071e+02])
```

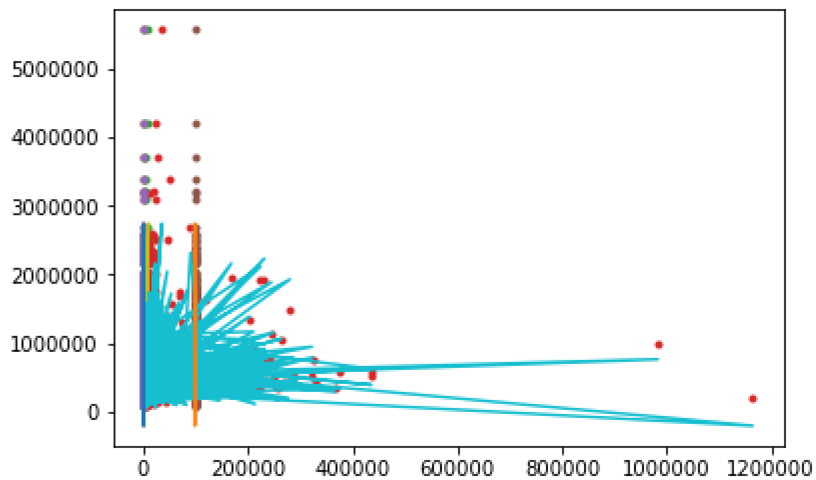
we can view the learned regression intercept.

In [109]:
```
my_features_model.intercept_
```

Out[109]:
```
-60558259.0181381
```

In [110]:
```python
import matplotlib.pyplot as plt
%matplotlib inline
plt.plot(test_data[my_features],
         test_data['price'],'.',
         test_data[my_features],
         my_features_model.predict(test_data[my_features]),
         '-')
```

Out[110]:
```
[<matplotlib.lines.Line2D at 0x26890390>,
 <matplotlib.lines.Line2D at 0x268904e0>,
 <matplotlib.lines.Line2D at 0x268905f8>,
 <matplotlib.lines.Line2D at 0x268906a0>,
 <matplotlib.lines.Line2D at 0x26890748>,
 <matplotlib.lines.Line2D at 0x268907f0>,
 <matplotlib.lines.Line2D at 0x2679b9b0>,
 <matplotlib.lines.Line2D at 0x2679bb00>,
 <matplotlib.lines.Line2D at 0x2679bba8>,
 <matplotlib.lines.Line2D at 0x2679bc50>,
 <matplotlib.lines.Line2D at 0x2679bcf8>,
 <matplotlib.lines.Line2D at 0x2679bda0>]
```



The RMSE goes down from 248.879 to $244, 004$ 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 [111]:
```
house1 = sales[sales['zipcode']==98039]
```

In [112]:
```
sales1 = sales[(sales['sqft_living']>=2000) & (sales['sqft_living']<=4000)]
```

In [113]:
```
house1
```

Out[113]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft_ab
2974	3625049014	20140829T000000	2950000	4	3.50	4860	23885	2.0	0	0	...	12	4
3761	2540700110	20150212T000000	1905000	4	3.50	4210	18564	2.0	0	0	...	11	4
4077	3262300940	20141107T000000	875000	3	1.00	1220	8119	1.0	0	0	...	7	1
4078	3262300940	20150210T000000	940000	3	1.00	1220	8119	1.0	0	0	...	7	1
4149	6447300265	20141014T000000	4000000	4	5.50	7080	16573	2.0	0	0	...	12	5
4411	2470100110	20140804T000000	5570000	5	5.75	9200	35069	2.0	0	0	...	13	6
4791	2210500019	20150324T000000	937500	3	1.00	1320	8500	1.0	0	0	...	7	1
5178	6447300345	20150406T000000	1160000	4	3.00	2680	15438	2.0	0	2	...	8	2
5589	6447300225	20141106T000000	1880000	3	2.75	2620	17919	1.0	0	1	...	9	2
5880	2525049148	20141007T000000	3418800	5	5.00	5450	20412	2.0	0	0	...	11	5
6868	3262300235	20141126T000000	1555000	5	2.50	2870	16238	2.0	0	0		8	

In [114]:
```
print(house1['price'].mean(axis = 0))
```

2160606.6

Question 2. What part of the houses people can live in between 2000 sq.ft. and 4000 sq.ft.?(Filtering data)

9221/21613 = 4.2631

In [115]:
```
len(sales1['sqft_living'])
```
Out[115]: 9221

In [116]:
```
len(sales['sqft_living'])
```
Out[116]: 21613

In [143]:
```
len(sales1['sqft_living'])/len(sales['sqft_living'])
```
Out[143]: 0.0

In [144]:
```
fraction_having_sqft_in_this_range = round(len(sales1['sqft_living'])/len(sales['sqft_living']),4)
print("result", fraction_having_sqft_in_this_range)
```
```
('result', 0.0)
```

In [118]:
```
print(my_features_model.predict(house1[my_features].values))
```
```
[1384843.10736139 1178118.09243258  254421.79147591  254421.79147591
 2120440.69150774 2740522.99811769  286352.32920416  683254.71535523
  719558.83034125 1534919.48302726  681756.52635602  608079.10238914
  738150.77685993 2928248.02630226  358507.96900482  612054.05025923
  946869.51667522 1300481.58748982  619687.0724642   321117.85412794
  996588.89227536 1261104.5727083   877024.05329502  853132.5098375
  696770.945676   1245130.94030382 1164413.39762525 1012002.00996201
  876099.96638316 1162701.8528327  1372930.38748734 1123192.99750817
  568547.18082173 1604711.01208086  515557.12398984 1217671.38036113
 1200381.31147681  756386.13246851  867549.69641165 1932291.49921482
  537427.25052292 1141062.03427178  857211.44954737  799595.48067813
 1558972.00346244 1104986.46296058 1131615.74355458  887617.28608844
 1442208.78247172 1049145.8889581 ]
```

In [ ]:

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 [119]:
```
house2 = sales.loc[sales['id']==1925069082]
```

In [120]:
```
house2
```

Out[120]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft_above
1361	1925069082	20150511T000000	2200000	5	4.25	4640	22703	2.0	1	4	...	8	2860

1 rows × 21 columns

In [121]:
```
print(sqft_model.predict(np.reshape(house2["sqft_living"].values, [-1, 1])))
```

```
[1269357.04273158]
```

In [122]:
```
print(my_features_model.predict(house2[my_features].values))
```

```
[1274443.76531347]
```

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 [123]:
```
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 [70]:
```
bill_gates=pandas.DataFrame.from_dict(bill_gates)
print(my_features_model.predict(bill_gates[my_features].values))
```

```
[15796988.23574059]
```

The model predicts a price of over $15M 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 [ ]: