In [2]:
```
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
%matplotlib inline
```

In [3]:
```
from sklearn.datasets import fetch_openml
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import make_column_transformer
from sklearn.svm import LinearSVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import cross_val_score
import warnings
warnings.filterwarnings("ignore")
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import validation_curve
from sklearn.model_selection import KFold

from sklearn.impute import SimpleImputer
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Ridge
from sklearn.linear_model import Lasso
from sklearn.linear_model import ElasticNet
```

# 2.1

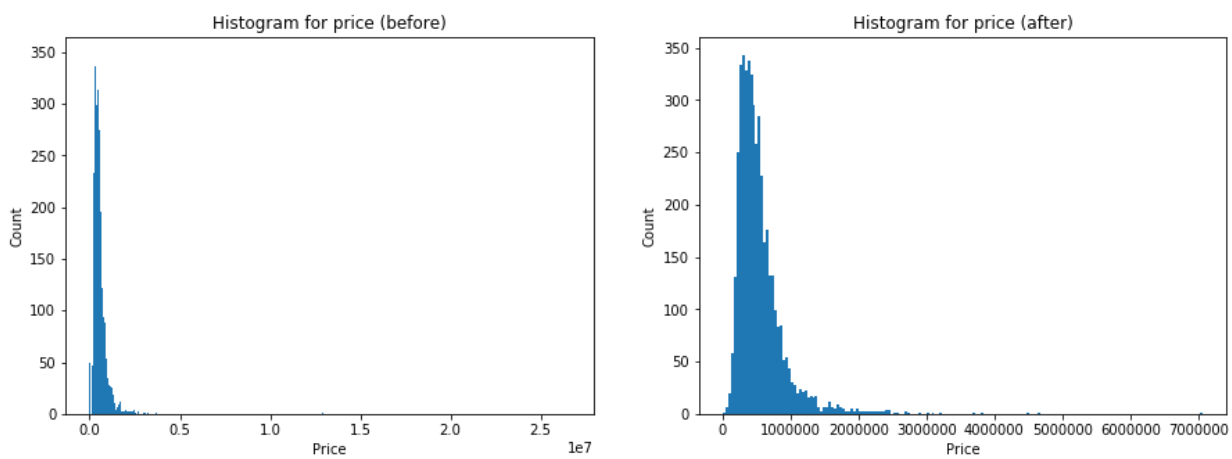
For target 'price', I will remove 4 outliers of 'price' and 0s, which contain no information.

In [4]:
```
df_temp = pd.read_csv('data.csv')
df_temp = df_temp.drop(['date'], axis=1)
#remove outliers of 'price' and 0s, which contain no information.
df = df_temp.loc[(df_temp['price'] != 0) & (df_temp['price'] < 1000000
0), :]
X = df.iloc[:,1:]
y = pd.DataFrame(df.iloc[:,0])
print(df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 4549 entries, 0 to 4599
Data columns (total 17 columns):
price            4549 non-null float64
bedrooms         4549 non-null float64
bathrooms        4549 non-null float64
sqft_living      4549 non-null int64
sqft_lot         4549 non-null int64
floors           4549 non-null float64
waterfront       4549 non-null int64
view             4549 non-null int64
condition        4549 non-null int64
sqft_above       4549 non-null int64
sqft_basement    4549 non-null int64
yr_built         4549 non-null int64
yr_renovated     4549 non-null int64
street           4549 non-null object
city             4549 non-null object
statezip         4549 non-null object
country          4549 non-null object
dtypes: float64(4), int64(9), object(4)
memory usage: 639.7+ KB
None
```

In [5]:

```
df_temp = pd.read_csv('data.csv')
df_temp = df_temp.drop(['date'], axis=1)

df = df_temp.loc[(df_temp['price'] != 0) & (df_temp['price'] < 1000000
0), :]
X = df.iloc[:,1:]
y = pd.DataFrame(df.iloc[:,0])
fig1, ax1 = plt.subplots(1, 2, figsize = (15,5))
ax1[0].hist(df_temp['price'], bins='auto');
ax1[0].set_title('Histogram for price (before)')
ax1[0].set_xlabel('Price')
ax1[0].set_ylabel('Count')
ax1[1].hist(y['price'], bins='auto');
ax1[1].set_title('Histogram for price (after)')
ax1[1].set_xlabel('Price')
ax1[1].set_ylabel('Count');
```




In [6]:

```
print('Continuous variables: ', list(df.columns[df.dtypes != 'object']
))
print('Categorical variables: ', list(df.columns[df.dtypes == 'object'
]))
```

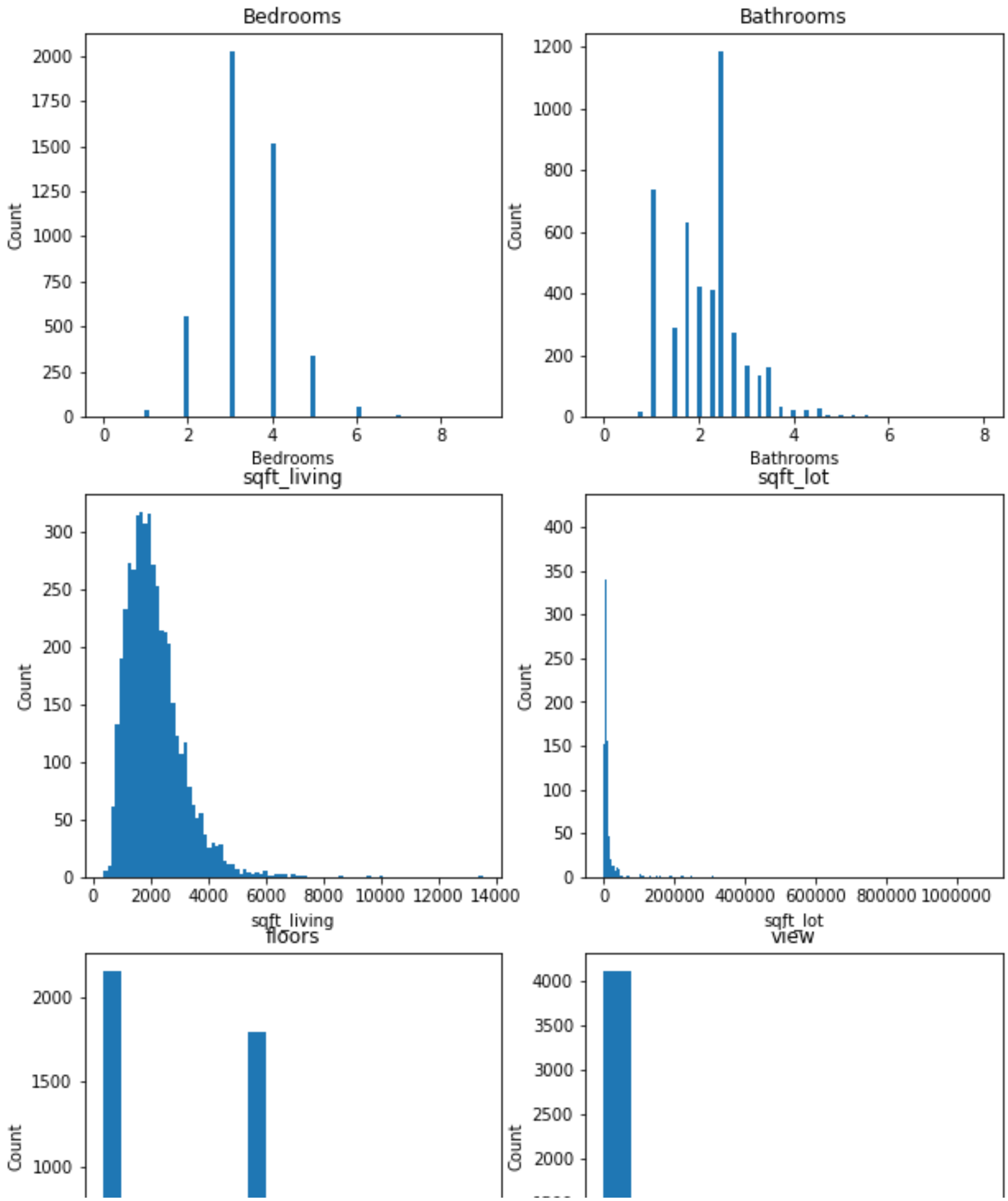
```
Continuous variables:  ['price', 'bedrooms', 'bathrooms', 'sqft_livi
ng', 'sqft_lot', 'floors', 'waterfront', 'view', 'condition', 'sqft_
above', 'sqft_basement', 'yr_built', 'yr_renovated']
Categorical variables:  ['street', 'city', 'statezip', 'country']
```

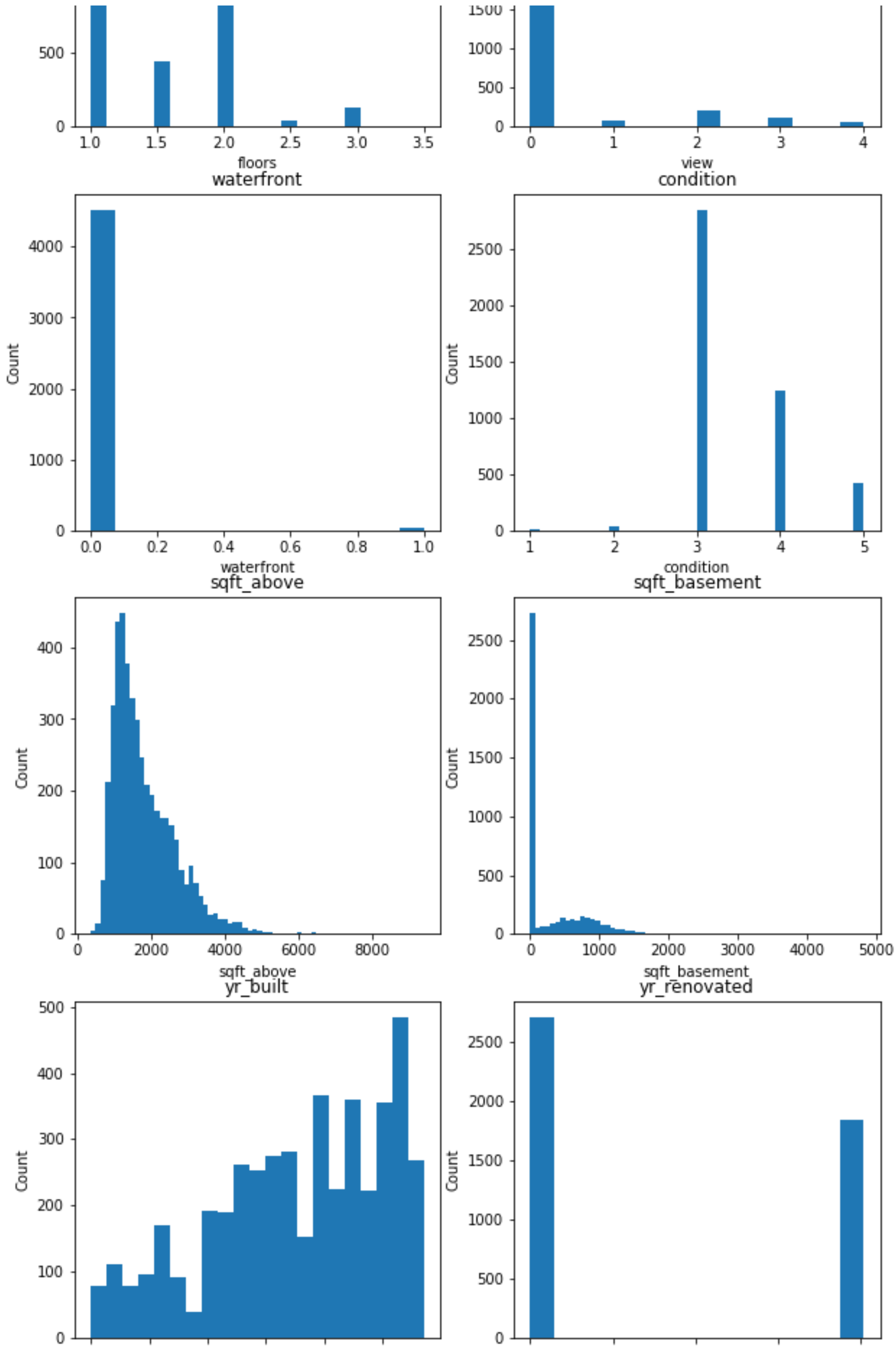
In [7]:

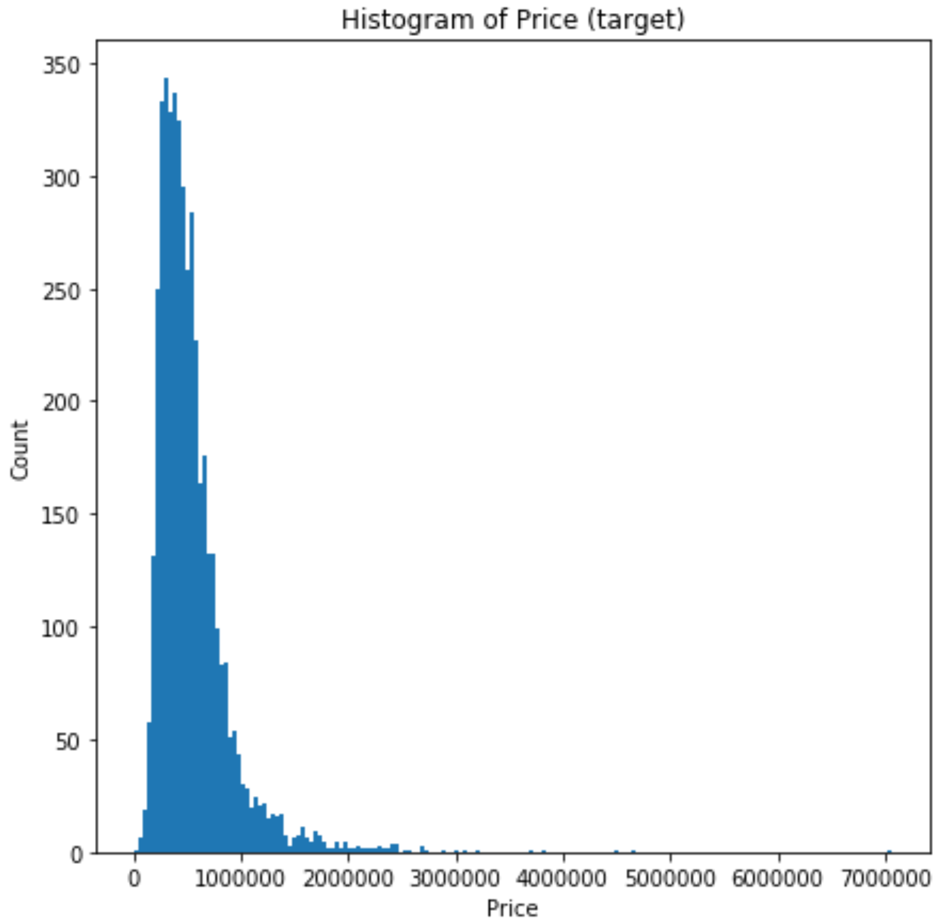
```
fig, ax = plt.subplots(6, 2, figsize = (10, 30))

ax[0,0].hist(X['bedrooms'], bins = 'auto')
ax[0,0].set_title("Bedrooms")
ax[0,0].set_xlabel('Bedrooms')
ax[0,0].set_ylabel('Count')

ax[0,1].hist(X['bathrooms'], bins = 'auto')
```

```
ax[0,1].set_title("Bathrooms")
ax[0,1].set_xlabel('Bathrooms')
ax[0,1].set_ylabel('Count')


ax[1,0].hist(X['sqft_living'], bins = 'auto')
ax[1,0].set_title("sqft_living")
ax[1,0].set_xlabel('sqft_living')
ax[1,0].set_ylabel('Count')

ax[1,1].hist(X['sqft_lot'], bins = 'auto')
ax[1,1].set_title("sqft_lot")
ax[1,1].set_xlabel('sqft_lot')
ax[1,1].set_ylabel('Count')

ax[2,0].hist(X['floors'], bins = 'auto')
ax[2,0].set_title("floors")
ax[2,0].set_xlabel('floors')
ax[2,0].set_ylabel('Count')

ax[2,1].hist(X['view'], bins = 'auto')
ax[2,1].set_title("view")
ax[2,1].set_xlabel('view')
ax[2,1].set_ylabel('Count')

ax[3,0].hist(X['waterfront'], bins = 'auto')
ax[3,0].set_title("waterfront")
ax[3,0].set_xlabel('waterfront')
ax[3,0].set_ylabel('Count')

ax[3,1].hist(X['condition'], bins = 'auto')
ax[3,1].set_title("condition")
ax[3,1].set_xlabel('condition')
ax[3,1].set_ylabel('Count')

ax[4,0].hist(X['sqft_above'], bins = 'auto')
ax[4,0].set_title("sqft_above")
ax[4,0].set_xlabel('sqft_above')
ax[4,0].set_ylabel('Count')

ax[4,1].hist(X['sqft_basement'], bins = 'auto')
ax[4,1].set_title("sqft_basement")
ax[4,1].set_xlabel('sqft_basement')
ax[4,1].set_ylabel('Count')

ax[5,0].hist(X['yr_built'], bins = 'auto')
ax[5,0].set_title("yr_built")
ax[5,0].set_xlabel('yr_built')
ax[5,0].set_ylabel('Count')
```

```
ax[5,1].hist(X['yr_renovated'], bins = 'auto')
ax[5,1].set_title("yr_renovated")
ax[5,1].set_xlabel('yr_renovated')
ax[5,1].set_ylabel('Count');

figa, axa = plt.subplots(1, 1, figsize = (7, 7))
axa.hist(y['price'], bins = 'auto')
axa.set_title("Histogram of Price (target)");
axa.set_xlabel('Price')
axa.set_ylabel('Count');
```



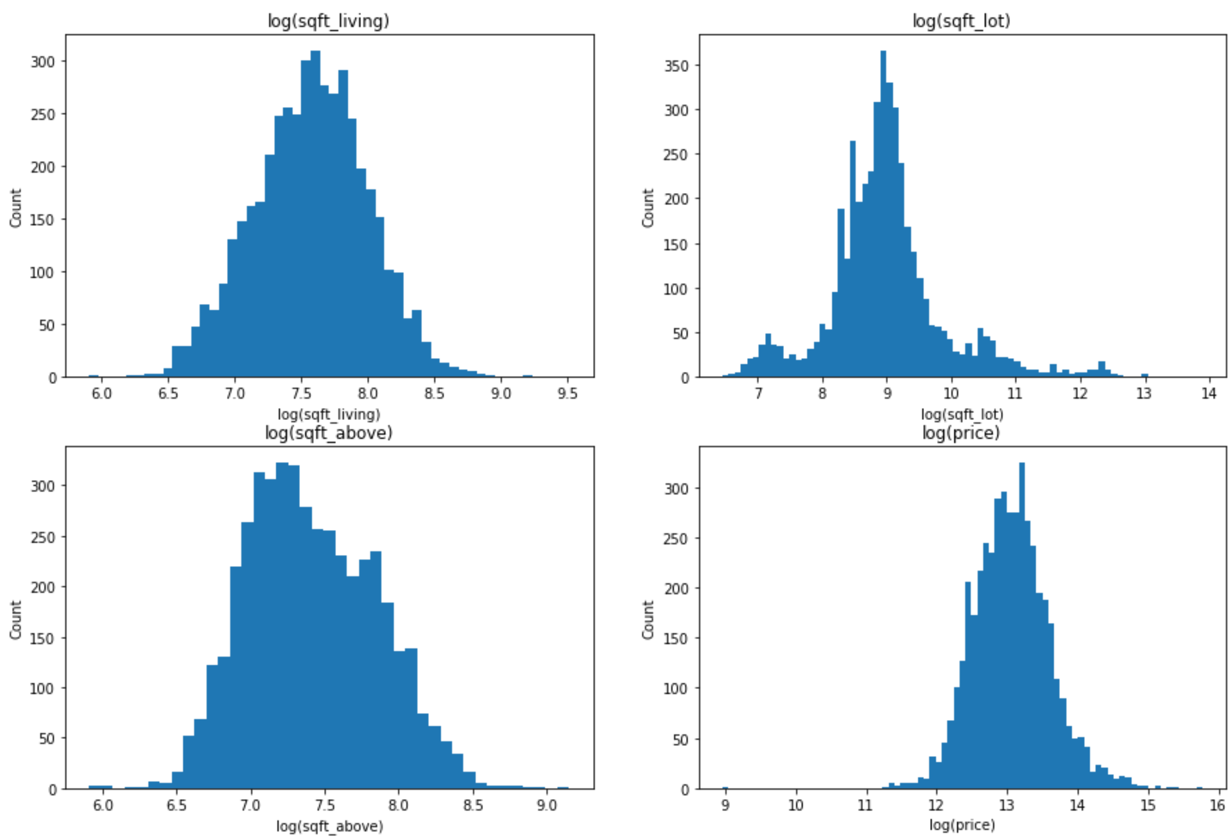

floors
view
waterfront
condition
Count
waterfront
condition
sqft_above
sqft_basement
Count
sqft_above
sqft_basement
yr_built
yr_renovated
Count


'sqrt_living', 'sqrt_lot','sqrt_above' and 'price' are heavily right-skewed. I will take log of these values to deal with the skewness. After taking log, the histogram of these columns look like below:

In [9]:
```
fig2, ax2 = plt.subplots(2, 2, figsize = (15, 10))
ax2[0,0].hist(np.log(X['sqft_living']), bins = 'auto')
ax2[0,0].set_title("log(sqft_living)")
ax2[0,0].set_xlabel('log(sqft_living)')
ax2[0,0].set_ylabel('Count')

ax2[0,1].hist(np.log(X['sqft_lot']), bins = 'auto')
ax2[0,1].set_title("log(sqft_lot)")
ax2[0,1].set_xlabel('log(sqft_lot)')
ax2[0,1].set_ylabel('Count')

ax2[1,0].hist(np.log(X['sqft_above']), bins = 'auto')
ax2[1,0].set_title("log(sqft_above)")
ax2[1,0].set_xlabel('log(sqft_above)')
ax2[1,0].set_ylabel('Count')

ax2[1,1].hist(np.log(y['price']), bins = 'auto');
ax2[1,1].set_title("log(price)")
ax2[1,1].set_xlabel('log(price)')
ax2[1,1].set_ylabel('Count')
```

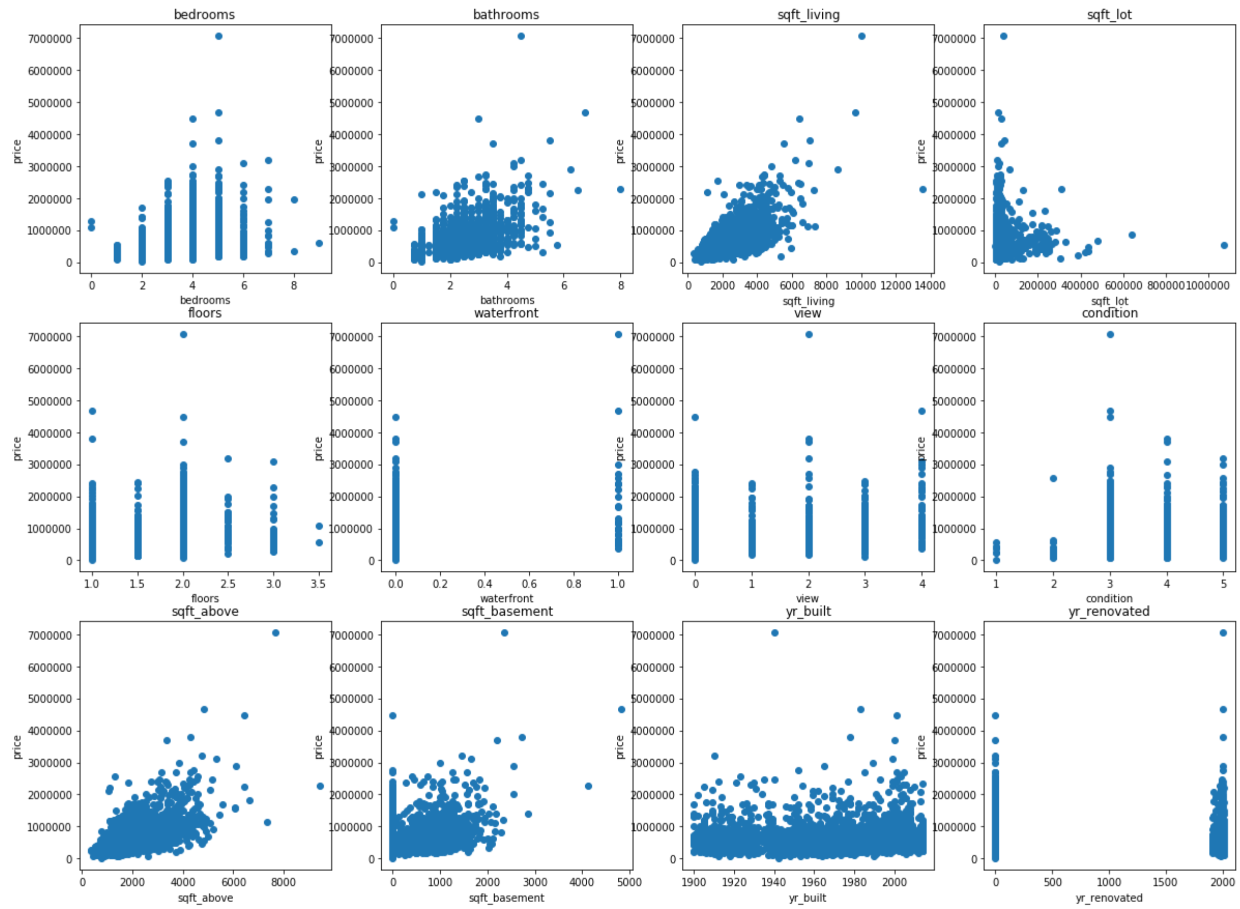
Out[9]:
```
Text(0, 0.5, 'Count')
```



## 2.3

In [10]:

```
fig3, ax3 = plt.subplots(3, 4, figsize = (20, 15))
cont_var = ['bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot',
            'floors', 'waterfront', 'view', 'condition',
            'sqft_above', 'sqft_basement', 'yr_built', 'yr_renovated']

for i in range(12):
    if i<=3:
        ax3[0,i].scatter(X[cont_var[i]], y['price']);
        ax3[0,i].set_title(cont_var[i])
        ax3[0,i].set_xlabel(cont_var[i])
        ax3[0,i].set_ylabel('price')
    elif 4<=i<=7:
        ax3[1,i-4].scatter(X[cont_var[i]], y['price']);
        ax3[1,i-4].set_title(cont_var[i])
        ax3[1,i-4].set_xlabel(cont_var[i])
        ax3[1,i-4].set_ylabel('price')
    else:
        ax3[2,i-8].scatter(X[cont_var[i]], y['price']);
        ax3[2,i-8].set_title(cont_var[i])
        ax3[2,i-8].set_xlabel(cont_var[i])
        ax3[2,i-8].set_ylabel('price')
```




# 2.4

I will drop columns 'country' and 'street'. Because 'country' only has 'USA', which is not informative; 'street' has too many categories, which is also not so useful in modeling.

In [11]:
```
X = X.drop(columns=['country', 'street'])
cat_var = ['city', 'statezip']
categorical = X.dtypes == object
continuous = X.dtypes != object
```

In [12]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state
= 123)
```

In [13]:
```
pipe_cate = make_pipeline(SimpleImputer(strategy='constant', fill_valu
e='NA'),
                          OneHotEncoder(handle_unknown='ignore'))

pipe_cont = make_pipeline(StandardScaler(),
                        SimpleImputer())
```

In [14]:
```
pre_notscaled = make_column_transformer((pipe_cate, categorical),
                                        (SimpleImputer(), ~categorical)
)

pre_scaled = make_column_transformer((pipe_cont, ~categorical),
                                     (pipe_cate, categorical))

preprocessor = {'scaled':pre_scaled, 'not scaled': pre_notscaled}
```

In [15]:
```
regressor = {'OLS': LinearRegression(),
        'Ridge':Ridge(),
        'Lasso':Lasso(),
        'ElasticNet':ElasticNet()}

for regression_name, regression in regressor.items():
    for preprocess_name, preprocess in preprocessor.items():
        pipe = make_pipeline(preprocess, regression)
        mean_cv_score = np.mean(cross_val_score(pipe, X_train, y_train
)).round(5)
        print('The mean cross validation score of {} {} is {}'
              .format(preprocess_name, regression_name,mean_cv_score))
```

```
The mean cross validation score of scaled OLS is 0.75218
The mean cross validation score of not scaled OLS is 0.75146
The mean cross validation score of scaled Ridge is 0.75308
The mean cross validation score of not scaled Ridge is 0.50727
The mean cross validation score of scaled Lasso is 0.75223
The mean cross validation score of not scaled Lasso is 0.75223
The mean cross validation score of scaled ElasticNet is 0.57225
The mean cross validation score of not scaled ElasticNet is 0.57121
```

By comparing mean cross validation score of scaled and non scaled data, we observe that scaling does improve cv score for most of regressions, though some improvements are minor. Note that Lasso does not have any improvement by scaling data.

We will use scaled data for following questions.

# 2.5

In [16]:
```
##Ridge
param_r = {'ridge__alpha': np.logspace(-4, 4, 9)}
pipe_r =  make_pipeline(pre_scaled, Ridge())
grid_r = GridSearchCV(pipe_r, param_r, cv = 10,
                      return_train_score = True)
grid_r.fit(X_train, y_train)
print("Ridge: best parameters: ", grid_r.best_params_)
print("Ridge: best mean cross-validation score: ", grid_r.best_score_)
```

```
Ridge: best parameters:  {'ridge__alpha': 1.0}
Ridge: best mean cross-validation score:  0.7569730622905126
```

In [17]:
```
##Lasso
param_l = {'lasso__alpha':np.logspace(-3, 3, 7)}
pipe_l =  make_pipeline(pre_scaled, Lasso())
grid_l = GridSearchCV(pipe_l, param_l, cv = 10,
                      return_train_score = True)
grid_l.fit(X_train, y_train)
print("Lasso: best parameters: ", grid_l.best_params_)
print("Lasso: best mean cross-validation score: ", grid_l.best_score_)
```

```
Lasso: best parameters:  {'lasso__alpha': 100.0}
Lasso: best mean cross-validation score:  0.7568187591885047
```

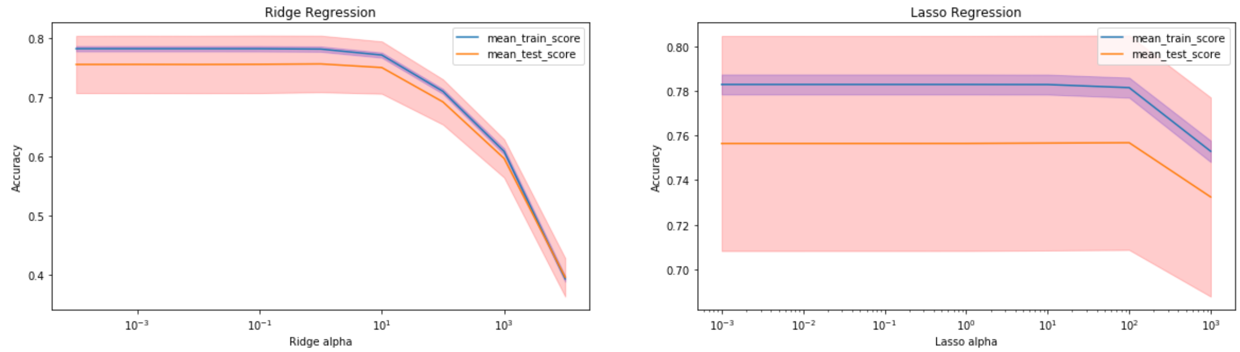
In [18]:
```
##ElasticNet
param_e = {'elasticnet__alpha':np.logspace(-3, 3, 7),
           'elasticnet__l1_ratio':np.arange(0, 1, 0.2)}
pipe_e =  make_pipeline(pre_scaled, ElasticNet())
grid_e = GridSearchCV(pipe_e, param_e, cv = 10,
                      return_train_score = True)
grid_e.fit(X_train, y_train)
print("ElasticNet: best parameters: ", grid_e.best_params_)
print("ElasticNet: best mean cross-validation score: ", grid_e.best_sc
ore_)
```

```
ElasticNet: best parameters:  {'elasticnet__alpha': 0.001, 'elasticn
et__l1_ratio': 0.4}
ElasticNet: best mean cross-validation score:  0.7574611047740805
```

In [19]:
```
#plot
figg, axx = plt.subplots(1,2, figsize=(20,5))
##Ridge
mean_train_scores_r = grid_r.cv_results_['mean_train_score']
std_train_scores_r  = grid_r.cv_results_['std_train_score']
```

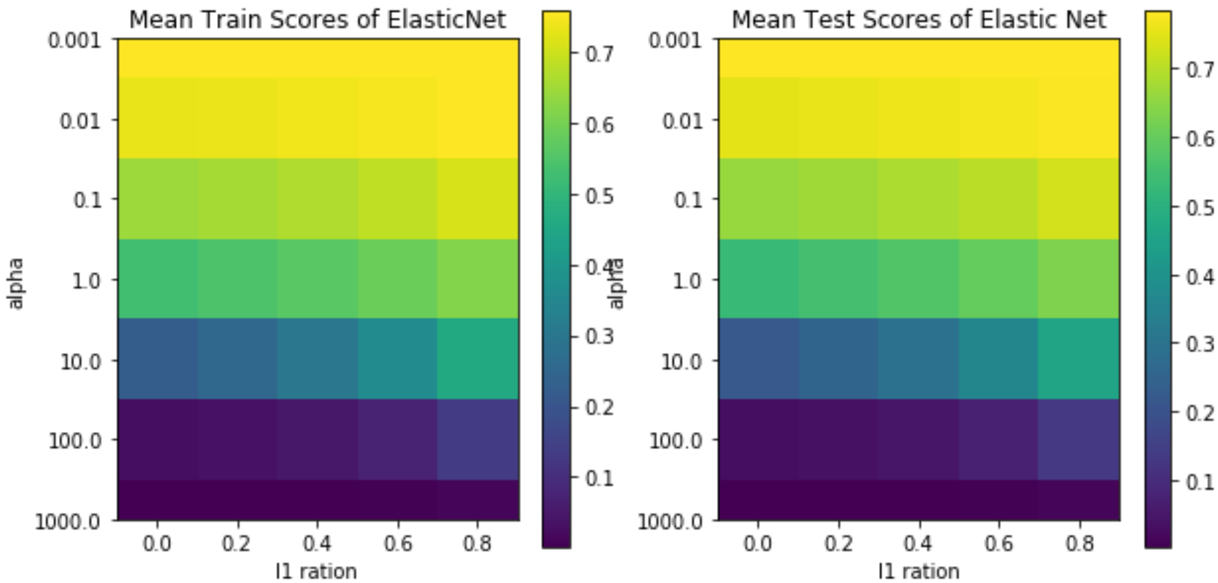
```
mean_test_scores_r  = grid_r.cv_results_['mean_test_score']
std_test_scores_r   = grid_r.cv_results_['std_test_score']




axx[0].semilogx(np.logspace(-4, 4, 9), mean_train_scores_r, label = "m
ean_train_score");

axx[0].fill_between(np.logspace(-4, 4, 9),
                    mean_train_scores_r - std_train_scores_r,
                    mean_train_scores_r + std_train_scores_r,
                    alpha=0.2, color='b');

axx[0].semilogx(np.logspace(-4, 4, 9), mean_test_scores_r , label = "m
ean_test_score");

axx[0].fill_between(np.logspace(-4, 4, 9),
                       mean_test_scores_r - std_test_scores_r,
                       mean_test_scores_r + std_test_scores_r,
                       alpha=0.2, color='r');
axx[0].legend();
axx[0].set_xlabel('Ridge alpha');
axx[0].set_ylabel('Accuracy');
axx[0].set_title('Ridge Regression');



# LASSO plot
mean_train_scores_l = grid_l.cv_results_['mean_train_score']
std_train_scores_l  = grid_l.cv_results_['std_train_score']
mean_test_scores_l  = grid_l.cv_results_['mean_test_score']
std_test_scores_l   = grid_l.cv_results_['std_test_score']

axx[1].semilogx(np.logspace(-3, 3, 7), mean_train_scores_l, label = "m
ean_train_score");

axx[1].fill_between(np.logspace(-3, 3, 7),
                    mean_train_scores_l - std_train_scores_l,
                    mean_train_scores_l + std_train_scores_l,
                    alpha=0.2, color='b');

axx[1].semilogx(np.logspace(-3, 3, 7), mean_test_scores_l , label = "m
ean_test_score");

axx[1].fill_between(np.logspace(-3, 3, 7),
                       mean_test_scores_l - std_test_scores_l,
                       mean_test_scores_l + std_test_scores_l,
                       alpha=0.2, color='r');
axx[1].legend();
```

```
axx[1].set_xlabel('Lasso alpha');
axx[1].set_ylabel('Accuracy');
axx[1].set_title('Lasso Regression');
```




In [20]:
```
##ElasticNet
df_e=pd.DataFrame(grid_e.cv_results_).loc[:,['param_elasticnet__alpha'
,'param_elasticnet__l1_ratio',
        'mean_test_score','mean_train_score']]
fige, axe = plt.subplots(1,2,figsize=(10,5))
fige.colorbar(axe[0].imshow(np.array(df_e.iloc[:,2]).reshape(7,5)),
              ax=axe[0])
axe[0].set_xticks(np.arange(5))
axe[0].set_xticklabels(np.round(np.arange(0, 1, 0.2),1))
axe[0].set_yticks(np.arange(7))
axe[0].set_yticklabels(np.logspace(-3, 3, 7))
axe[0].set_title('Mean Train Scores of ElasticNet')
axe[0].set_xlabel('l1 ration')
axe[0].set_ylabel('alpha')

fige.colorbar(axe[1].imshow(np.array(df_e.iloc[:,-1]).reshape(7,5)),
              ax=axe[1])
axe[1].set_xticks(np.arange(5))
axe[1].set_xticklabels(np.round(np.arange(0, 1, 0.2),1))
axe[1].set_yticks(np.arange(7))
axe[1].set_yticklabels(np.logspace(-3, 3, 7))
axe[1].set_title('Mean Test Scores of Elastic Net')
axe[1].set_xlabel('l1 ration')
axe[1].set_ylabel('alpha')
```

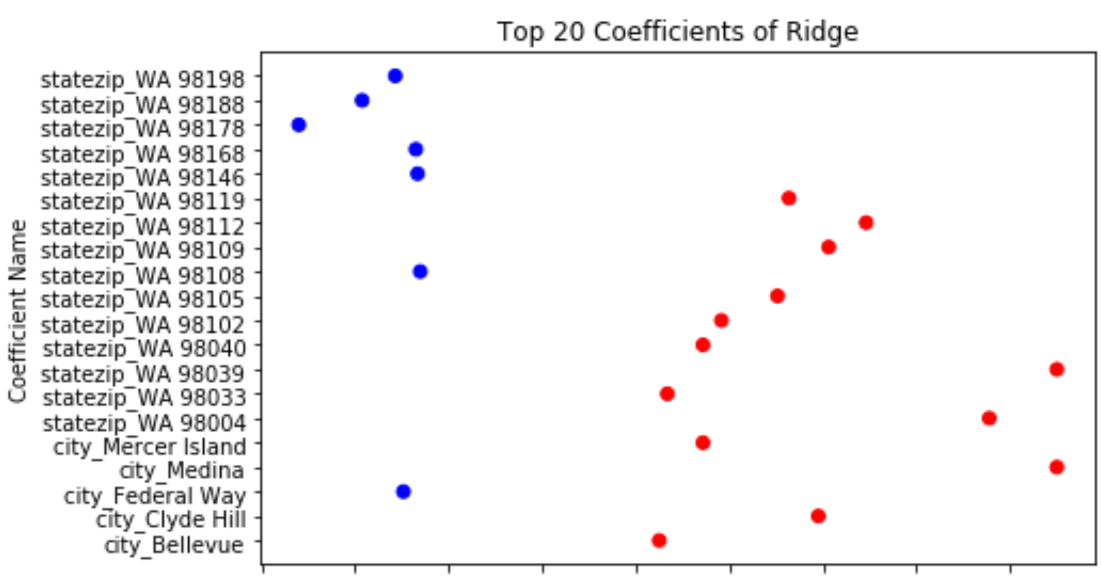
Out[20]: Text(0, 0.5, 'alpha')

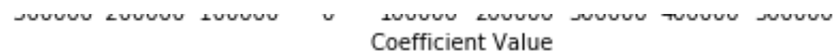


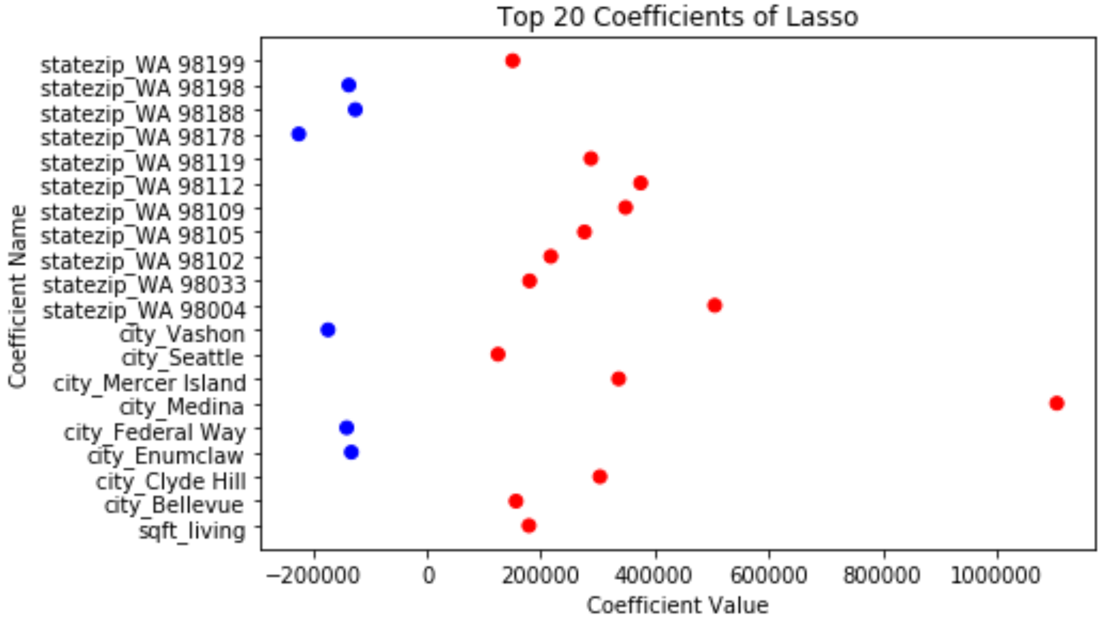

# 2.6

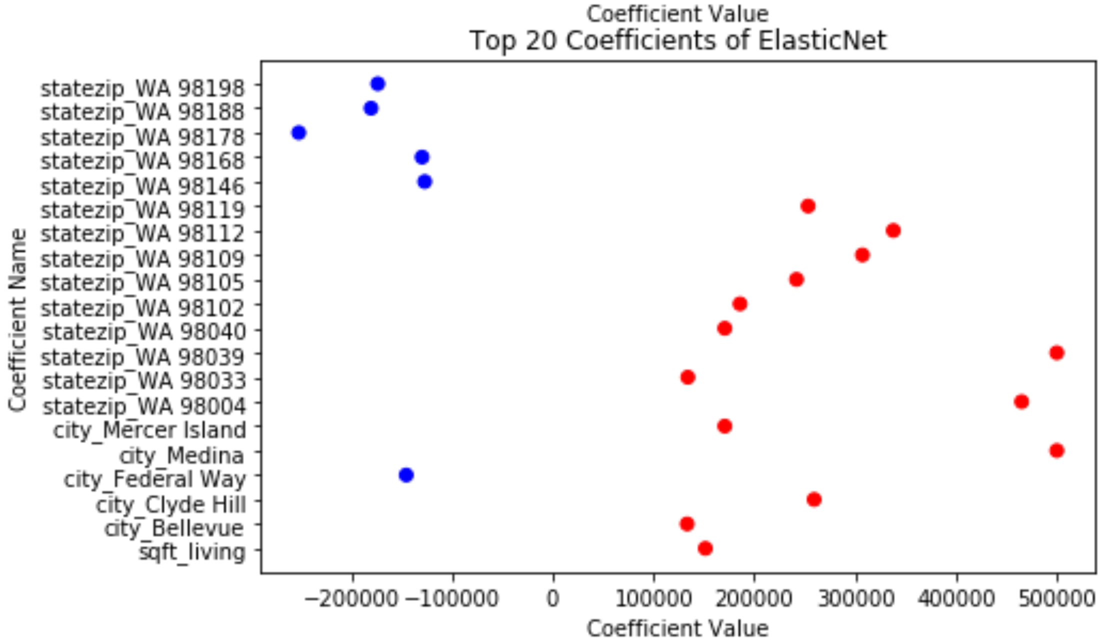
In [92]:
```
fig26, ax26 = plt.subplots(3, 1, figsize = (7, 15))
columns = pd.get_dummies(X).columns
#Ridge
coef_r = grid_r.best_estimator_[1].coef_[0]
idx_r = np.sort(np.abs(coef_r).argsort()[-20:][::-1])
ax26[0].scatter(coef_r[idx_r],columns[idx_r], c = np.sign(coef_r[idx_r
]), cmap='bwr')
ax26[0].set_title('Top 20 Coefficients of Ridge')
ax26[0].set_xlabel('Coefficient Value')
ax26[0].set_ylabel('Coefficient Name')


#Lasso
coef_l = grid_l.best_estimator_[1].coef_
idx_l = np.sort(np.abs(coef_l).argsort()[-20:][::-1])
ax26[1].scatter(coef_l[idx_l],columns[idx_l], c = np.sign(coef_l[idx_l
]), cmap='bwr')
ax26[1].set_title('Top 20 Coefficients of Lasso')
ax26[1].set_xlabel('Coefficient Value')
ax26[1].set_ylabel('Coefficient Name')


#ElasticNet
coef_e = grid_e.best_estimator_[1].coef_
idx_e = np.sort(np.abs(coef_e).argsort()[-20:][::-1])
ax26[2].scatter(coef_e[idx_e],columns[idx_e], c = np.sign(coef_e[idx_e
]), cmap='bwr')
ax26[2].set_title('Top 20 Coefficients of ElasticNet')
ax26[2].set_xlabel('Coefficient Value')
ax26[2].set_ylabel('Coefficient Name')
```

Out[92]:
```
Text(0, 0.5, 'Coefficient Name')
```




Coefficient Value


Top 20 Coefficients of Lasso
Coefficient Name
statezip_WA 98199
statezip_WA 98198
statezip_WA 98188
statezip_WA 98178
statezip_WA 98119
statezip_WA 98112
statezip_WA 98109
statezip_WA 98105
statezip_WA 98102
statezip_WA 98033
statezip_WA 98004
city_Vashon
city_Seattle
city_Mercer Island
city_Medina
city_Federal Way
city_Enumclaw
city_Clyde Hill
city_Bellevue
sqft_living
−200000
0
200000
400000
600000
800000
1000000
Coefficient Value


Top 20 Coefficients of ElasticNet
Coefficient Name
statezip_WA 98198
statezip_WA 98188
statezip_WA 98178
statezip_WA 98168
statezip_WA 98146
statezip_WA 98119
statezip_WA 98112
statezip_WA 98109
statezip_WA 98105
statezip_WA 98102
statezip_WA 98040
statezip_WA 98039
statezip_WA 98033
statezip_WA 98004
city_Mercer Island
city_Medina
city_Federal Way
city_Clyde Hill
city_Bellevue
sqft_living
−200000
−100000
0
100000
200000
300000
400000
500000
Coefficient Value

In [ ]: