In [1]:

```
%matplotlib inline

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns


import datetime
import random

from sklearn.model_selection import train_test_split, cross_val_score, KFold
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score, mean_squared_error, mean_absolute_error


seed = 309
random.seed(seed)
np.random.seed(seed)
```

In [2]:

```
df = pd.read_csv("/Users/keirynhart/Documents/Uni/Comp 309/Assignment 4/data/Part 1 - regression/diamonds.csv")
df.describe()
```

Out[2]:

	Unnamed: 0	carat	depth	table	x	y
count	53940.000000	53940.000000	53940.000000	53940.000000	53940.000000	53940.000000
mean	26970.500000	0.797940	61.749405	57.457184	5.731157	5.734526
std	15571.281097	0.474011	1.432621	2.234491	1.121761	1.142135
min	1.000000	0.200000	43.000000	43.000000	0.000000	0.000000
25%	13485.750000	0.400000	61.000000	56.000000	4.710000	4.720000
50%	26970.500000	0.700000	61.800000	57.000000	5.700000	5.710000
75%	40455.250000	1.040000	62.500000	59.000000	6.540000	6.540000
max	53940.000000	5.010000	79.000000	95.000000	10.740000	58.900000

In [3]:

```
df.isnull().values.any()
```

Out[3]:

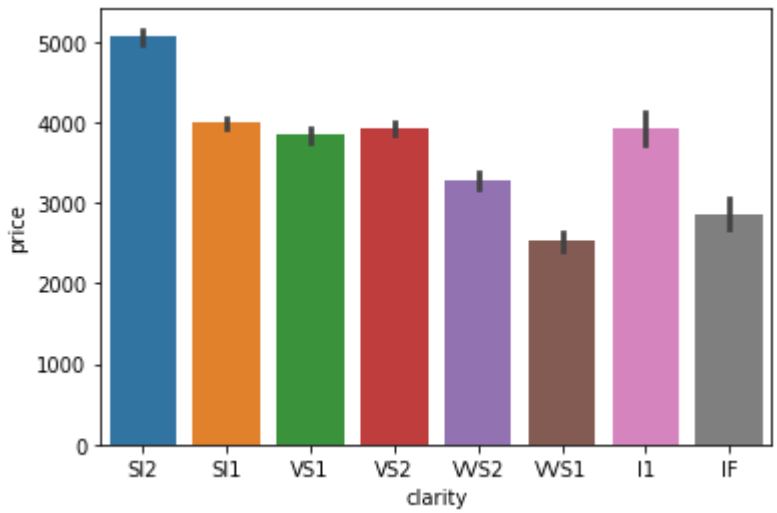
```
False
```

In [4]:

```
#sns.barplot(x = "cut", y = "price", data = df)
#sns.barplot(x = "color", y = "price", data = df)
sns.barplot(x = "clarity", y = "price", data = df)
```

Out[4]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fe9ca33d790>
```



Changing variables:

In [5]:

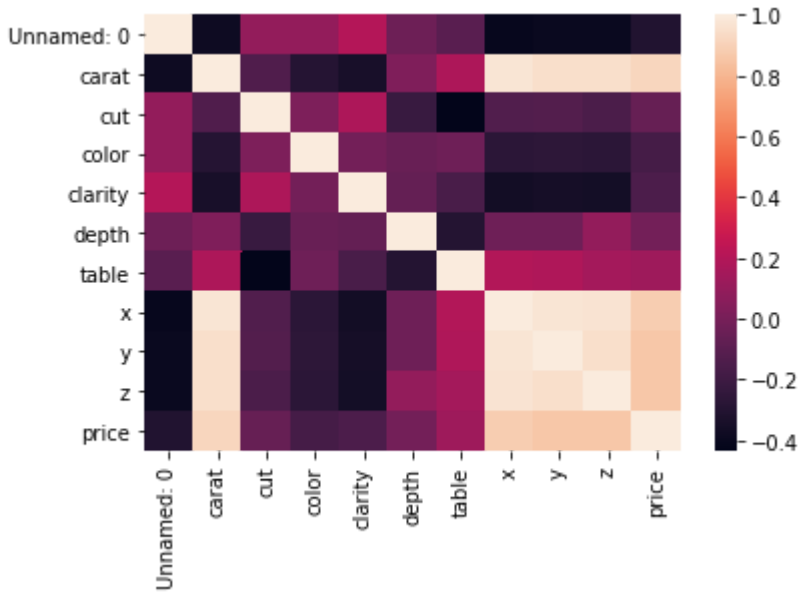
```
df['cut'] = df['cut'].apply(lambda x: 1 if x=='Fair' else(2 if x=='Good'
                                        else(3 if x=='Very Good'
                                        else(4 if x=='Premium' else 5))))

df['color'] = df['color'].apply(lambda x: 1 if x=='J' else(2 if x=='I'
                                       else(3 if x=='H'
                                       else(4 if x=='G'
                                       else(5 if x=='F'
                                       else(6 if x=='E' else 7))))))

df['clarity'] = df['clarity'].apply(lambda x: 1 if x=='I1' else(2 if x=='SI2'
                                       else(3 if x=='SI1'
                                       else(4 if x=='VS2'
                                       else(5 if x=='VS1'
                                       else(6 if x=='WS2'
                                       else 7 if x=='WS1' else 8))))))
```

In [6]:

```
sns.heatmap(df.corr())
```

Out[6]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fe9ca1b0b50>
```



Training and Testing:

In [7]:

```
train_data, test_data = train_test_split(df, test_size = 0.3, random_state = see
d)
```

In [8]:

```
train_data.describe()
```

Out[8]:

	Unnamed: 0	carat	cut	color	clarity	depth
count	37758.000000	37758.000000	37758.000000	37758.000000	37758.000000	37758.000000
mean	26932.728137	0.798166	3.903438	4.412045	4.302717	61.741557
std	15561.556646	0.472857	1.113829	1.700652	2.052403	1.426374
min	3.000000	0.200000	1.000000	1.000000	1.000000	43.000000
25%	13448.250000	0.400000	3.000000	3.000000	3.000000	61.000000
50%	26890.500000	0.700000	4.000000	4.000000	4.000000	61.800000
75%	40425.750000	1.040000	5.000000	6.000000	5.000000	62.500000
max	53940.000000	5.010000	5.000000	7.000000	8.000000	79.000000

In [9]:

```
test_data.describe()
```

Out[9]:

	Unnamed: 0	carat	cut	color	clarity	depth
count	16182.000000	16182.000000	16182.000000	16182.000000	16182.000000	16182.000000
mean	27058.634347	0.797413	3.905636	4.391237	4.315721	61.767717
std	15594.073336	0.476709	1.123071	1.702125	2.061084	1.446973
min	1.000000	0.200000	1.000000	1.000000	1.000000	50.800000
25%	13626.750000	0.400000	3.000000	3.000000	3.000000	61.100000
50%	27138.000000	0.700000	4.000000	4.000000	4.000000	61.800000
75%	40520.250000	1.040000	5.000000	6.000000	5.000000	62.500000
max	53939.000000	4.000000	5.000000	7.000000	8.000000	79.000000

In [10]:

```
train_labels = train_data['price']

#copy
train_data_full = train_data.copy()

train_data = train_data.drop(['price'], axis = 1)
```

In [11]:

```
test_labels = test_data["price"]

#copy
test_data_full = test_data.copy()


#drop price
test_data = test_data.drop(['price'], axis = 1)
```

In [12]:

```
print('Linear regression:')

lr = LinearRegression()
lr.fit(train_data, train_labels)

y_pred = lr.predict(test_data)

coef = lr.coef_
intercept = lr.intercept_

print("coefficients: ", coef)
print("intercept: ", intercept)

lr.score(test_data, test_labels)

lr_mse = mean_squared_error(test_labels, y_pred)
lr_r2 = lr.score(test_data, test_labels)
lr_mae = mean_absolute_error(test_labels, y_pred)

print("MSE: ", "%.2f" % lr_mse)
print("RMSE: {error}".format(error = "%.2f" % np.sqrt(lr_mse)))
print("r2: ", "%.2f" % lr_r2)
print("MAE: ", "%.2f" % lr_mae)



print('K-neighbours regression:')

from sklearn.neighbors import KNeighborsRegressor

kn = KNeighborsRegressor(n_neighbors = 2)

kn.fit(train_data, train_labels)

y_pred1 = kn.predict(test_data)



kn.score(test_data, test_labels)

kn_mse = mean_squared_error(test_labels, y_pred1)
kn_r2 = kn.score(test_data, test_labels)
kn_mae = mean_absolute_error(test_labels, y_pred1)

print("MSE: ", "%.2f" % kn_mse)
print("RMSE: {error}".format(error = "%.2f" % np.sqrt(kn_mse)))
print("r2: ", "%.3f" % kn_r2)
print("MAE: ", "%.2f" % kn_mae)

print('Ridge Regression:')


from sklearn.linear_model import Ridge

ridge = Ridge()

ridge.fit(train_data, train_labels)

y_pred2 = ridge.predict(test_data)
```

```
ridge.score(test_data, test_labels)

ridge_mse = mean_squared_error(test_labels, y_pred2)
ridge_r2 = ridge.score(test_data, test_labels)
ridge_mae = mean_absolute_error(test_labels, y_pred2)

print("MSE: ", "%.2f" % ridge_mse)
print("RMSE: {error}".format(error = "%.2f" % np.sqrt(ridge_mse)))
print("r2: ", "%.2f" % ridge_r2)
print("MAE: ", "%.2f" % ridge_mae)

print('decision Tree Regression:')


from sklearn.tree import DecisionTreeRegressor

tree = DecisionTreeRegressor(max_depth=2)

tree.fit(train_data, train_labels)

y_pred3 = tree.predict(test_data)

tree.score(test_data, test_labels)

tree_mse = mean_squared_error(test_labels, y_pred3)
tree_r2 = tree.score(test_data, test_labels)
tree_mae = mean_absolute_error(test_labels, y_pred3)

print("MSE: ", "%.2f" % tree_mse)
print("RMSE: {error}".format(error = "%.2f" % np.sqrt(tree_mse)))
print("r2: ", "%.2f" % tree_r2)
print("MAE: ", "%.2f" % tree_mae)

print('Random Forest Regression:')


from sklearn.ensemble import RandomForestRegressor

rf = RandomForestRegressor(max_depth=2, random_state=0)

rf.fit(train_data, train_labels)

y_pred4 = rf.predict(test_data)

rf.score(test_data, test_labels)

rf_mse = mean_squared_error(test_labels, y_pred4)
rf_r2 = rf.score(test_data, test_labels)
rf_mae = mean_absolute_error(test_labels, y_pred4)

print("MSE: ", "%.2f" % rf_mse)
print("RMSE: {error}".format(error = "%.2f" % np.sqrt(rf_mse)))
print("r2: ", "%.2f" % rf_r2)
print("MAE: ", "%.2f" % rf_mae)

print('Gradient Boost Regression:')

from sklearn.ensemble import GradientBoostingRegressor

gradient = GradientBoostingRegressor()
```

```
gradient.fit(train_data, train_labels)

y_pred5 = gradient.predict(test_data)

gradient.score(test_data, test_labels)

gradient_mse = mean_squared_error(test_labels, y_pred5)
gradient_r2 = gradient.score(test_data, test_labels)
gradient_mae = mean_absolute_error(test_labels, y_pred5)

print("MSE: ", "%.2f" % gradient_mse)
print("RMSE: {error}".format(error = "%.2f" % np.sqrt(gradient_mse)))
print("r2: ", "%.3f" % gradient_r2)
print("MAE: ", "%.2f" % gradient_mae)

print('SGD Regression:')


from sklearn.linear_model import SGDRegressor
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import StandardScaler

SGD = make_pipeline(StandardScaler(), SGDRegressor(max_iter=1000))

SGD.fit(train_data, train_labels)

y_pred6 = SGD.predict(test_data)

SGD.score(test_data, test_labels)

SGD_mse = mean_squared_error(test_labels, y_pred6)
SGD_r2 = SGD.score(test_data, test_labels)
SGD_mae = mean_absolute_error(test_labels, y_pred6)

print("MSE: ", "%.2f" % SGD_mse)
print("RMSE: {error}".format(error = "%.2f" % np.sqrt(SGD_mse)))
print("r2: ", "%.2f" % SGD_r2)
print("MAE: ", "%.2f" % SGD_mae)

print('SVR Regression:')

from sklearn.svm import SVR

svr = make_pipeline(StandardScaler(), SVR(C=1.0, epsilon=0.2))

svr.fit(train_data, train_labels)

y_pred7 = svr.predict(test_data)

svr.score(test_data, test_labels)

svr_mse = mean_squared_error(test_labels, y_pred7)
svr_r2 = svr.score(test_data, test_labels)
svr_mae = mean_absolute_error(test_labels, y_pred7)

print("MSE: ", "%.2f" % svr_mse)
print("RMSE: {error}".format(error = "%.2f" % np.sqrt(svr_mse)))
print("r2: ", "%.2f" % svr_r2)
print("MAE: ", "%.2f" % svr_mae)
```

```
print('Linear SVR Regression:')

#svr_lin = SVR(kernel='linear', C=100, gamma='auto')
svr_lin = make_pipeline(StandardScaler(), SVR(kernel = 'linear', C=1.0, epsilon=
0.2, gamma = 'auto'))

svr_lin.fit(train_data, train_labels)

y_pred8 = svr_lin.predict(test_data)

svr_lin.score(test_data, test_labels)

svr_lin_mse = mean_squared_error(test_labels, y_pred8)
svr_lin_r2 = svr_lin.score(test_data, test_labels)
svr_lin_mae = mean_absolute_error(test_labels, y_pred8)

print("MSE: ", "%.2f" % svr_lin_mse)
print("RMSE: {error}".format(error = "%.2f" % np.sqrt(svr_lin_mse)))
print("r2: ", "%.2f" % svr_lin_r2)
print("MAE: ", "%.2f" % svr_lin_mae)

print('Multilayer Perceptron Regression:')

from sklearn.neural_network import MLPRegressor

MLP = MLPRegressor(random_state=1, max_iter=500)

MLP.fit(train_data, train_labels)

y_pred9 = MLP.predict(test_data)

MLP.score(test_data, test_labels)

MLP_mse = mean_squared_error(test_labels, y_pred9)
MLP_r2 = MLP.score(test_data, test_labels)
MLP_mae = mean_absolute_error(test_labels, y_pred9)

print("MSE: ", "%.2f" % MLP_mse)
print("RMSE: {error}".format(error = "%.2f" % np.sqrt(MLP_mse)))
print("r2: ", "%.2f" % MLP_r2)
print("MAE: ", "%.2f" % MLP_mae)

table = {'Name':  ['linear regression', 'k-neighbors regression', 'Ridge regress
ion', 'decision tree regression', 'random forest regression', 'gradient Boosting
regression', 'SGD regression', 'support vector regression', 'linear SVR', 'multi
-layer perceptron regression'],
         'MSE': [lr_mse, kn_mse, ridge_mse, tree_mse, rf_mse, gradient_mse, SGD_
mse, svr_mse, svr_lin_mse, MLP_mse],
         'RMSE': [np.sqrt(lr_mse), np.sqrt(kn_mse), np.sqrt(ridge_mse), np.sqrt(
tree_mse), np.sqrt(rf_mse), np.sqrt(gradient_mse), np.sqrt(SGD_mse), np.sqrt(svr
_mse), np.sqrt(svr_lin_mse), np.sqrt(MLP_mse)],
         'r2': [lr_r2, kn_r2, ridge_r2, tree_r2, rf_r2, gradient_r2, SGD_r2, svr
_r2, svr_lin_r2, MLP_r2],
         'MAE':[lr_mae, kn_mae, ridge_mae, tree_mae, rf_mae, gradient_mae, SGD_m
ae, svr_mae, svr_lin_mae, MLP_mae]}



table = pd.DataFrame (table, columns = ['Name','MSE','RMSE', 'r2', 'MAE'])
```

```
table['r2'] = table['r2'].round(3)
table['MSE'] = table['MSE'].round(2)
table['RMSE'] = table['RMSE'].round(2)
table['MAE'] = table['MAE'].round(2)
table
```

```
Linear regression:
coefficients:  [ 5.11432796e-03  1.06524125e+04  1.27265673e+02  3.0
6160702e+02
  3.72835470e+02 -8.06752989e+01 -2.81078165e+01 -8.33539554e+02
  2.48995494e+01 -1.91907434e+01]
intercept:  3138.5246568301427
MSE:  1603591.70
RMSE: 1266.33
r2:  0.90
MAE:  824.08
K-neighbours regression:
MSE:  56342.18
RMSE: 237.37
r2:  0.997
MAE:  17.64
Ridge Regression:
MSE:  1603583.40
RMSE: 1266.33
r2:  0.90
MAE:  824.54
decision Tree Regression:
MSE:  1881412.36
RMSE: 1371.65
r2:  0.88
MAE:  915.17
Random Forest Regression:
MSE:  1824077.58
RMSE: 1350.58
r2:  0.89
MAE:  901.43
Gradient Boost Regression:
MSE:  51293.66
RMSE: 226.48
r2:  0.997
MAE:  125.06
SGD Regression:
MSE:  1612405.44
RMSE: 1269.81
r2:  0.90
MAE:  829.02
SVR Regression:
MSE:  8126705.05
RMSE: 2850.74
r2:  0.50
MAE:  1338.80
Linear SVR Regression:
MSE:  2516693.59
RMSE: 1586.41
r2:  0.84
MAE:  854.06
MSE:  498109.19
RMSE: 705.77
r2:  0.97
MAE:  460.94
```

Out[12]:

	Name	MSE	RMSE	r2	MAE
0	linear regression	1603591.70	1266.33	0.901	824.08
1	k-neighbors regression	56342.18	237.37	0.997	17.64
2	Ridge regression	1603583.40	1266.33	0.901	824.54
3	decision tree regression	1881412.36	1371.65	0.884	915.17
4	random forest regression	1824077.58	1350.58	0.888	901.43
5	gradient Boosting regression	51293.66	226.48	0.997	125.06
6	SGD regression	1612405.44	1269.81	0.901	829.02
7	support vector regression	8126705.05	2850.74	0.499	1338.80
8	linear SVR	2516693.59	1586.41	0.845	854.06
9	multi-layer perceptron regression	498109.19	705.77	0.969	460.94

In [ ]: