EDA

In [ ]:
```
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
import seaborn as sns
%matplotlib inline
```

In [ ]:
```
df = pd.read_csv('Real estate.csv')
```

In [ ]:
```
df = df.drop('No', axis=1)
```

In [ ]:
```
df.isna().sum()
```

Out[ ]:
```
X1 transaction date                       0
X2 house age                              0
X3 distance to the nearest MRT station    0
X4 number of convenience stores           0
X5 latitude                               0
X6 longitude                              0
Y house price of unit area                0
dtype: int64
```

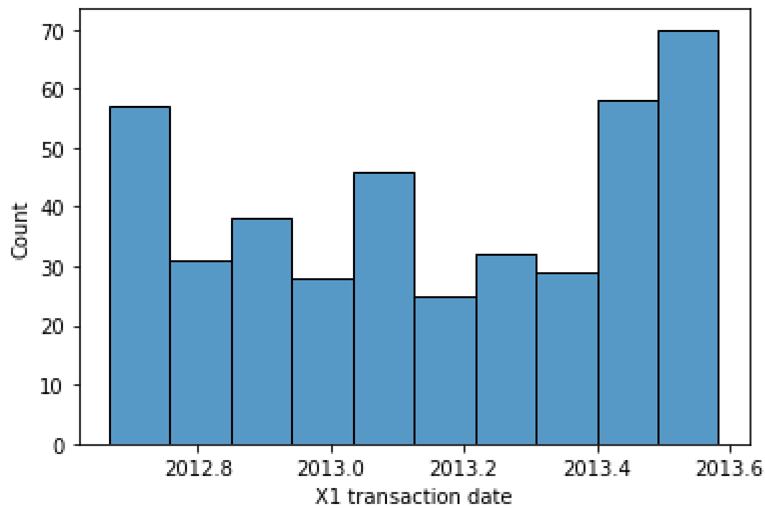
In [ ]:
```
df.describe()
```

Out[ ]:

	X1 transaction date	X2 house age	X3 distance to the nearest MRT station	X4 number of convenience stores	X5 latitude	X6 longitude	Y house price of unit area
count	414.000000	414.000000	414.000000	414.000000	414.000000	414.000000	414.000000
mean	2013.148971	17.712560	1083.885689	4.094203	24.969030	121.533361	37.980193
std	0.281967	11.392485	1262.109595	2.945562	0.012410	0.015347	13.606488
min	2012.667000	0.000000	23.382840	0.000000	24.932070	121.473530	7.600000
25%	2012.917000	9.025000	289.324800	1.000000	24.963000	121.528085	27.700000
50%	2013.167000	16.100000	492.231300	4.000000	24.971100	121.538630	38.450000
75%	2013.417000	28.150000	1454.279000	6.000000	24.977455	121.543305	46.600000
max	2013.583000	43.800000	6488.021000	10.000000	25.014590	121.566270	117.500000

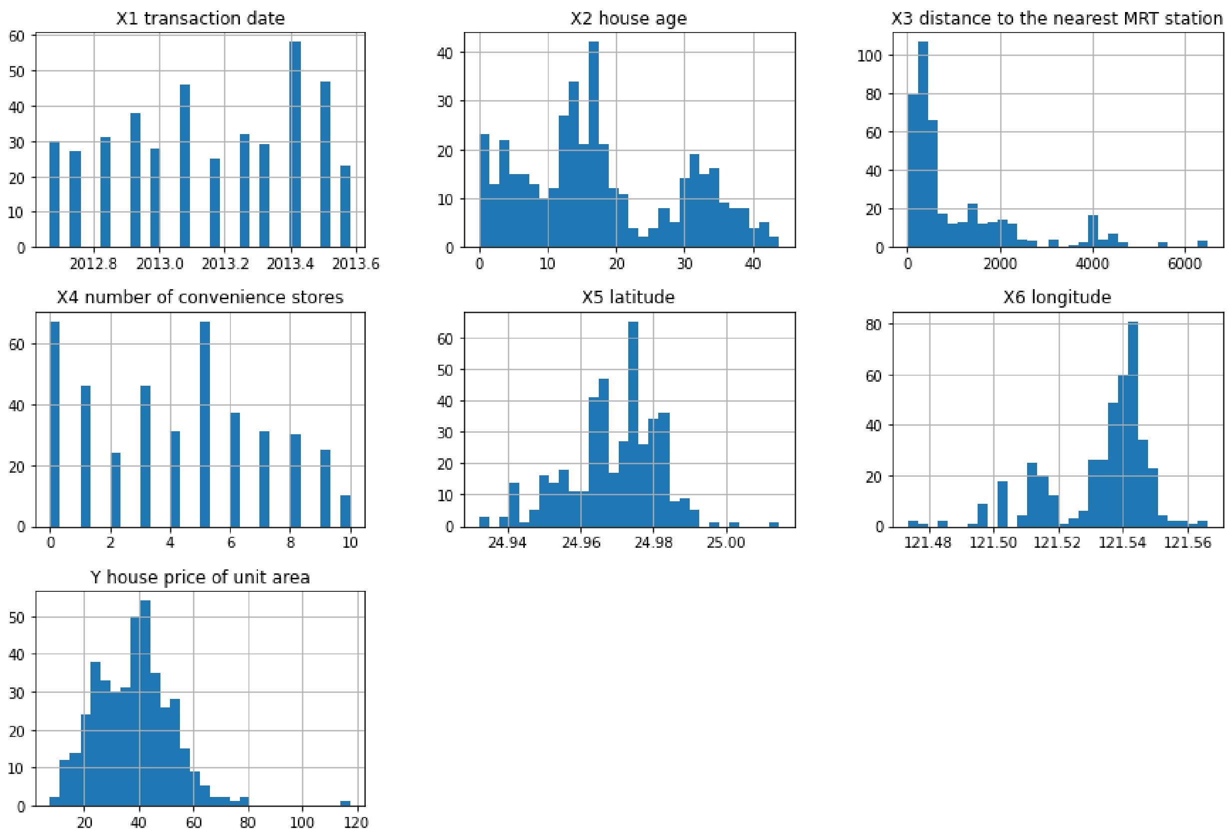
In [ ]:
```
sns.histplot(df['X1 transaction date'])
```

Out[ ]:
```
<AxesSubplot:xlabel='X1 transaction date', ylabel='Count'>
```



In [ ]:
```python
df.hist(bins=30, figsize=(15, 10))
```

Out[ ]:
```
array([[<AxesSubplot:title={'center':'X1 transaction date'}>,
        <AxesSubplot:title={'center':'X2 house age'}>,
        <AxesSubplot:title={'center':'X3 distance to the nearest MRT station'}>],
       [<AxesSubplot:title={'center':'X4 number of convenience stores'}>,
        <AxesSubplot:title={'center':'X5 latitude'}>,
        <AxesSubplot:title={'center':'X6 longitude'}>],
       [<AxesSubplot:title={'center':'Y house price of unit area'}>,
        <AxesSubplot:>, <AxesSubplot:>]], dtype=object)
```



In [ ]:
```python
df.corr()
```

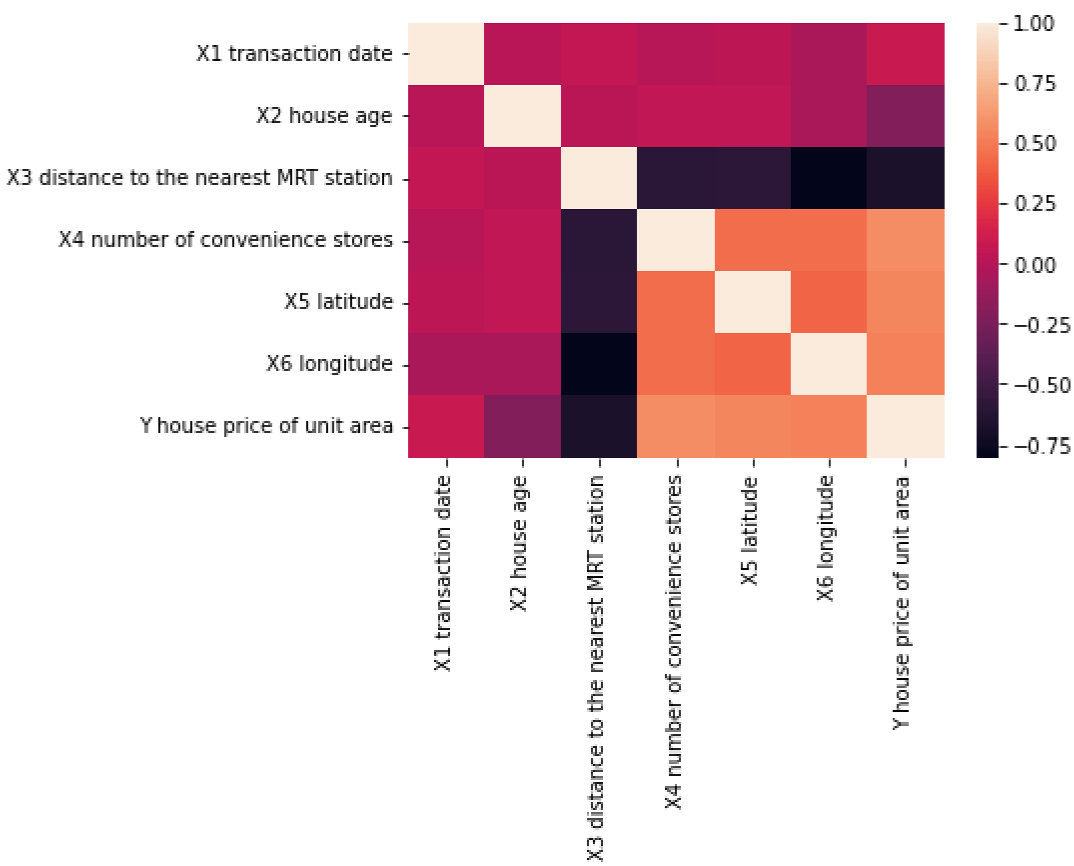
Out[ ]:

	X1 transaction date	X2 house age	X3 distance to the nearest MRT station	X4 number of convenience stores	X5 latitude	X6 longitude	Y house price of unit area
X1 transaction date	1.000000	0.017549	0.060880	0.009635	0.035058	-0.041082	0.087491
X2 house age	0.017549	1.000000	0.025622	0.049593	0.054420	-0.048520	-0.210567
X3 distance to the nearest MRT station	0.060880	0.025622	1.000000	-0.602519	-0.591067	-0.806317	-0.673613
X4 number of convenience stores	0.009635	0.049593	-0.602519	1.000000	0.444143	0.449099	0.571005
X5 latitude	0.035058	0.054420	-0.591067	0.444143	1.000000	0.412924	0.546307
X6 longitude	-0.041082	-0.048520	-0.806317	0.449099	0.412924	1.000000	0.523287
Y house price of unit area	0.087491	-0.210567	-0.673613	0.571005	0.546307	0.523287	1.000000

In [ ]:

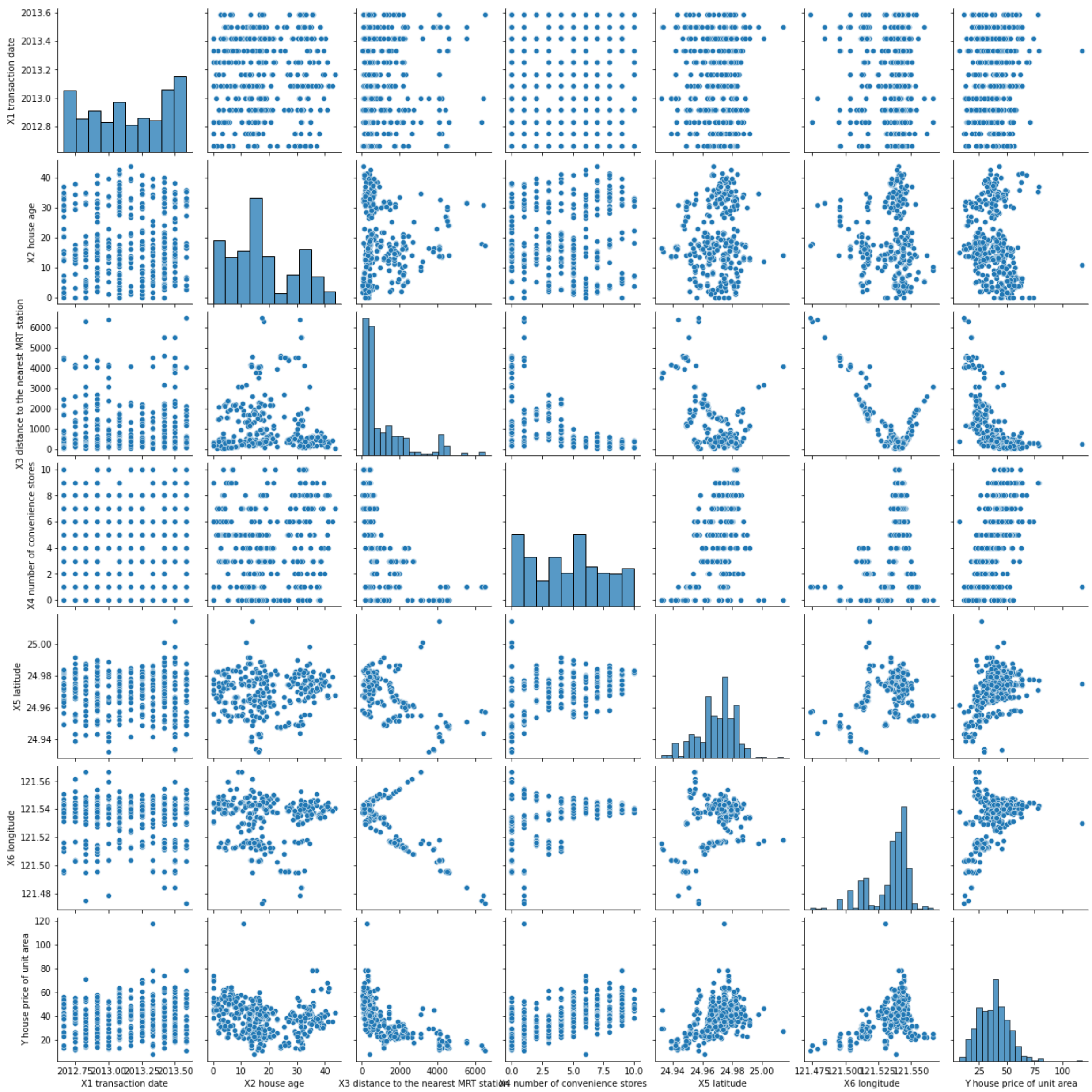
```
sns.heatmap(df.corr())
```

Out[ ]: <AxesSubplot:>



In [ ]:
```
sns.pairplot(df)
```

Out[ ]:
```
<seaborn.axisgrid.PairGrid at 0x25ab787bb80>
```



Decision to Normalize or Standardize

For this project, I have decided to normalize the data. This is because of a few reasons outlined below:

- The data is mostly not bell shaped. Some of the histograms as seen above are skewed and not useful when standardized
- The data for the different columns are all on different scales. This will cause the model to overtrain on specific columns.

In [ ]:
```
from sklearn import preprocessing
```

In [ ]:
```
normalized_df = preprocessing.normalize(df)
```

In [ ]:
```
normalized_df = pd.DataFrame(normalized_df)
```

In [ ]:
```
normalized_df = normalized_df.rename(columns={0: 'transaction date', 1: 'house age', 2
```

In [ ]:
```
normalized_df.describe()
```

Out[ ]:

	transaction date	house age	distance to the nearest MRT station	number of convenience stores	latitude	longitude	house price of unit area
count	414.000000	414.000000	414.000000	414.000000	414.000000	414.000000	414.000000
mean	0.871381	0.007671	0.358914	0.001930	0.010808	0.052606	0.017251
std	0.177865	0.005558	0.277563	0.001481	0.002208	0.010741	0.007984
min	0.296356	0.000000	0.011591	0.000000	0.003673	0.017878	0.001648
25%	0.809536	0.003407	0.141940	0.000491	0.010037	0.048880	0.010762
50%	0.969419	0.006338	0.237059	0.001919	0.012022	0.058524	0.018310
75%	0.987650	0.011414	0.584855	0.002960	0.012256	0.059630	0.022569
max	0.997753	0.021697	0.954898	0.004953	0.012377	0.060252	0.057702

Multiple Linear Regression

In [ ]:
```
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
```

In [ ]:
```
X = normalized_df.drop('house price of unit area', axis=1)
y = normalized_df['house price of unit area']
```

In [ ]:
```
from sklearn.feature_selection import RFE

NUM_FEATURES = 6
model = LinearRegression()
rfe = RFE(estimator=model, n_features_to_select=NUM_FEATURES)
fit = rfe.fit(X, y)
print("Num Features:", fit.n_features_)
print("Selected Features:", fit.support_)
print("Feature Ranking:", fit.ranking_)
# calculate the score for the selected features
score = rfe.score(X,y)
print("Model Score with selected features is: ", score)


#6 features gives a score of 0.784804
#5 features gives a score of 0.726227
```

```
Num Features: 6
Selected Features: [ True  True  True  True  True  True]
Feature Ranking: [1 1 1 1 1 1]
Model Score with selected features is:  0.7848041558917571
```

In [ ]:

```python
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=

modelLinReg = LinearRegression()

# Train the model
modelLinReg.fit(X_train, y_train)

# Use the model to make predictions
y_pred = modelLinReg.predict(X_test)

# Evaluate the model
mse = mean_squared_error(y_test, y_pred)

mse
```

Out[ ]:

```
6.487545482396875e-06
```

Now using OLS

In [ ]:

```python
import statsmodels.api as sm
```

In [ ]:

```python
X_train_with_constant = sm.add_constant(X_train)
X_test_with_constant = sm.add_constant(X_test)

# Create an OLS model
ols_model = sm.OLS(y_train, X_train_with_constant)

# Fit the model
ols_results = ols_model.fit()

# Use the model to make predictions
y_pred_ols = ols_results.predict(X_test_with_constant)

# Evaluate the model
mse_ols = mean_squared_error(y_test, y_pred_ols)

mse_ols
```

Out[ ]:

```
6.487545482401079e-06
```

In [ ]:

```python
def stepwise_selection(X, y,
                       initial_list=[],
                       threshold_in=0.01,
                       threshold_out = 0.05,
                       verbose=True):

        included = list(initial_list)
        while True:
            changed=False
            # forward step
            excluded = list(set(X.columns)-set(included))
            new_pval = pd.Series(index=excluded)
            for new_column in excluded:
```

```
                model = sm.OLS(y, sm.add_constant(pd.DataFrame(X[included+[new_column]
                new_pval[new_column] = model.pvalues[new_column]
            best_pval = new_pval.min()
            if best_pval < threshold_in:
                best_feature = new_pval.idxmin()
                included.append(best_feature)
                changed=True
                if verbose:
                    print('Add  {:30} with p-value {:.6}'.format(best_feature, best_pv

            # backward step
            model = sm.OLS(y, sm.add_constant(pd.DataFrame(X[included]))).fit()
            # use all coefs except intercept
            pvalues = model.pvalues.iloc[1:]
            worst_pval = pvalues.max() # null if pvalues is empty
            if worst_pval > threshold_out:
                changed=True
                worst_feature = pvalues.idxmax()
                included.remove(worst_feature)
                if verbose:
                    print('Drop {:30} with p-value {:.6}'.format(worst_feature, worst_
            if not changed:
                break
        return included

result = stepwise_selection(X, y)

print('resulting features:')
print(result)
```

```
Add  distance to the nearest MRT station with p-value 7.73786e-117
Add  house age                           with p-value 1.4763e-10
Add  number of convenience stores   with p-value 0.00146099
resulting features:
['distance to the nearest MRT station', 'house age', 'number of convenience stores']
```

```
C:\Users\manit\AppData\Local\Temp\ipykernel_3424\3179247796.py:24: FutureWarning: The
default dtype for empty Series will be 'object' instead of 'float64' in a future vers
ion. Specify a dtype explicitly to silence this warning.
  new_pval = pd.Series(index=excluded)
C:\Users\manit\AppData\Local\Temp\ipykernel_3424\3179247796.py:24: FutureWarning: The
default dtype for empty Series will be 'object' instead of 'float64' in a future vers
ion. Specify a dtype explicitly to silence this warning.
  new_pval = pd.Series(index=excluded)
C:\Users\manit\AppData\Local\Temp\ipykernel_3424\3179247796.py:24: FutureWarning: The
default dtype for empty Series will be 'object' instead of 'float64' in a future vers
ion. Specify a dtype explicitly to silence this warning.
  new_pval = pd.Series(index=excluded)
C:\Users\manit\AppData\Local\Temp\ipykernel_3424\3179247796.py:24: FutureWarning: The
default dtype for empty Series will be 'object' instead of 'float64' in a future vers
ion. Specify a dtype explicitly to silence this warning.
  new_pval = pd.Series(index=excluded)
```

In [ ]:

```
X_new = X[['distance to the nearest MRT station', 'house age', 'number of convenience

X_train_new, X_test_new, y_train_new, y_test_new = train_test_split(X, y, test_size=0.


X_train_new = sm.add_constant(X_train_new)
X_test_new = sm.add_constant(X_test_new)
```

```
# Create an OLS model
ols_model_changed = sm.OLS(y_train_new, X_train_new)

# Fit the model
ols_results = ols_model_changed.fit()

# Use the model to make predictions
y_pred_ols_new = ols_results.predict(X_test_new)

# Evaluate the model
mse_ols_new = mean_squared_error(y_test_new, y_pred_ols_new)

mse_ols_new
```

Out[ ]:

```
6.487545482401079e-06
```

Regularized Version of the Model

In [ ]:

```
from sklearn.linear_model import Ridge
from sklearn.linear_model import Lasso
from sklearn.model_selection import train_test_split
```

In [ ]:

```
rr = Ridge(alpha=0.0001)

rr.fit(X_train, y_train)
train_score=lr.score(X_train, y_train)
test_score=lr.score(X_test, y_test)
Ridge_train_score = rr.score(X_train,y_train)
Ridge_test_score = rr.score(X_test, y_test)
print("linear regression train score:", train_score)
print("linear regression test score:", test_score)
print( "ridge regression train score low alpha:", Ridge_train_score)
print("ridge regression test score low alpha:", Ridge_test_score)
```

```
linear regression train score: 0.7556980381762006
linear regression test score: 0.8708257024312931
ridge regression train score low alpha: 0.7264451247868773
ridge regression test score low alpha: 0.8416974915905153
```

In [ ]:

```
lasso = Lasso()
lasso.fit(X_train,y_train)
train_score=lasso.score(X_train,y_train)
test_score=lasso.score(X_test,y_test)
coeff_used = np.sum(lasso.coef_!=0)

lasso00001 = Lasso(alpha=0.00001, max_iter=10000)
lasso00001.fit(X_train,y_train)
train_score00001=lasso00001.score(X_train,y_train)
test_score00001=lasso00001.score(X_test,y_test)
coeff_used00001 = np.sum(lasso00001.coef_!=0)
print( "training score for alpha=0.0001:", train_score00001 )
print( "test score for alpha =0.0001: ", test_score00001)
```

```
training score for alpha=0.0001: 0.6943897854951754
test score for alpha =0.0001:  0.809082323468797 4
```

I can see by using Lasso and Ridge, the results I have obtained are better and have increased.

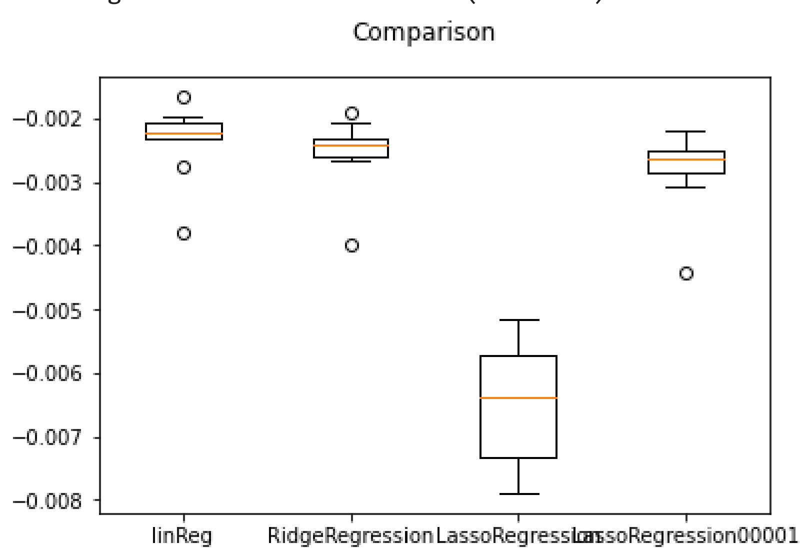
Cross Validation of all models

In [ ]:
```
from matplotlib import pyplot
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
```

In [ ]:
```
# prepare models
models = []

models.append(('linReg', modelLinReg))
models.append(('RidgeRegression', rr))
models.append(('LassoRegression', lasso))
models.append(('LassoRegression00001', lasso00001))
```

In [ ]:
```
results = []
names = []

for name, mod in models:
        kfold = KFold(n_splits=10, random_state=7, shuffle = True)
        cv_results = cross_val_score(mod, X, y, cv=kfold, scoring = 'neg_mean_absolute
        results.append(cv_results)
        names.append(name)
        msg = "%s: %f (%f)" % (name, cv_results.mean(), cv_results.std())
        print(msg)

fig = pyplot.figure()
fig.suptitle('Comparison')
ax = fig.add_subplot(111)
pyplot.boxplot(results)
ax.set_xticklabels(names)
pyplot.show()
```

```
linReg: -0.002344 (0.000555)
RidgeRegression: -0.002523 (0.000532)
LassoRegression: -0.006498 (0.000941)
LassoRegression00001: -0.002813 (0.000589)
```



Best Model

After doing cross validation on the different models, it can be seen that the linear regression model performs the best. I used negative mean squared error to evaluate the models, and the linear regression performed the best out of all the models.

f)

After doing cross-validation on the different models, it can be seen that the linear regression model performs the best. I used negative mean squared error to evaluate the models, and the linear regression performed the best out of all the models.

The way cross-validation works is by splitting X and y into 5 equal “folds”. The model is then trained on 4 of the folds and evaluated on the other left-out fold. This process is repeated 5 times, with each of the 5 folds only used once for validation. The cross_val_score function then returns a list of the scores from each of the 5 evaluations. This gives an accurate assessment of how the model performs on unseen data.

Because the regularization is used to prevent overfitting, it works best on larger datasets and not the ones we are working with on this project. This set doesn’t have an issue with overfitting and the plain linear regression model performs better.

High-variance models are overly complex and overfit on the data. Ridge and lasso regressions are techniques that reduce overfitting and reduce the complexity of the model. Because our dataset does not struggle with this, ridge and lasso does not perform well.

g)

After looking at the results from the Linear Regression model, OLS, Ridge Regression, and Lasso Regression, I do not find any discrepancies. The linear regression model has a r^2 value of 0.87 on the test set which is higher than any of the other models tested. It is not significantly greater, but is, on average, 1-2% greater than the other models. The OLS model performed the same as the Linear Regression Model.