Importing Essential Libraries

In [1]:

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
from sklearn import metrics
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.neighbors import KNeighborsRegressor
from sklearn.svm import SVR
import joblib
```

Importing Data

In [2]:

```
df = pd.read_csv('housing.csv')
df = df[~(df['MEDV'] >= 50.0)]
```

In [3]:

```
df.shape
```

Out[3]:

```
(490, 14)
```

In [4]:

```
X = df.drop('MEDV', axis = 1)
y = df['MEDV']
```

In [5]:

```
df.columns
```

Out[5]:

```
Index(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX',
'RM', 'AGE', 'DIS', 'RAD', 'TAX',
       'PTRATIO', 'B', 'LSTAT', 'MEDV'],
      dtype='object')
```

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In [6]:

```
df.head()
```

Out[6]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	
0	0.00632	18.0	2.31	0	0.538	6.575	65.2	4.0
1	0.02731	0.0	7.07	0	0.469	6.421	78.9	4.9
2	0.02729	0.0	7.07	0	0.469	7.185	61.1	4.9
3	0.03237	0.0	2.18	0	0.458	6.998	45.8	6.0
4	0.06905	0.0	2.18	0	0.458	7.147	54.2	6.0

In [7]:

```
df.isnull().sum()
```

Out[7]:

```
CRIM       0
ZN         0
INDUS      0
CHAS       0
NOX        0
RM         0
AGE        0
DIS        0
RAD        0
TAX        0
PTRATIO    0
B          0
```

```
LSTAT      0
MEDV       0
dtype: int64
```

In [8]:

```
df['CHAS'].value_counts()
```

Out[8]:

```
0    461
1     29
Name: CHAS, dtype: int64
```

In [9]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 490 entries, 0 to 505
Data columns (total 14 columns):
CRIM       490 non-null float64
ZN         490 non-null float64
INDUS      490 non-null float64
CHAS       490 non-null int64
NOX        490 non-null float64
RM         490 non-null float64
AGE        490 non-null float64
DIS        490 non-null float64
RAD        490 non-null int64
TAX        490 non-null int64
PTRATIO    490 non-null float64
B          490 non-null float64
LSTAT      490 non-null float64
MEDV       490 non-null float64
dtypes: float64(11), int64(3)
memory usage: 57.4 KB
```

In [10]:

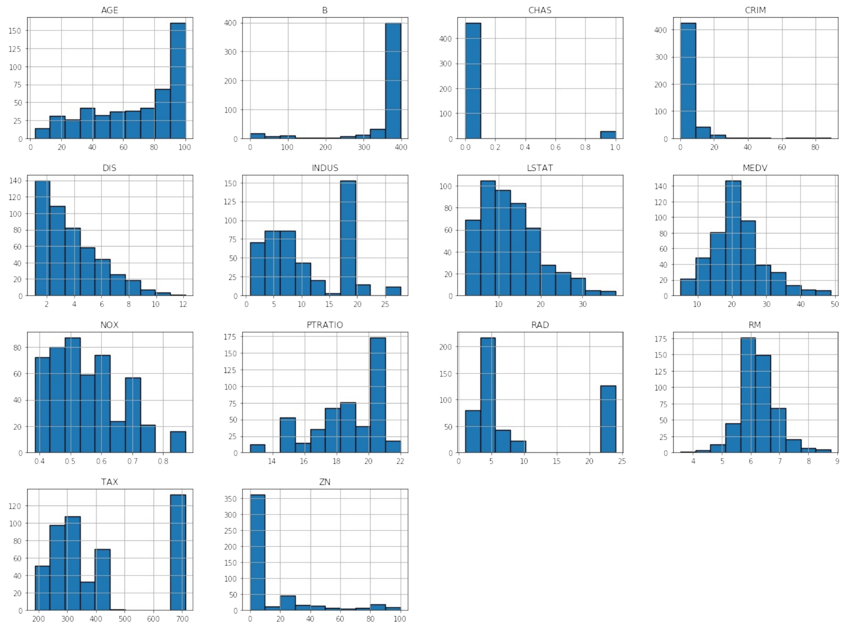
```
df.describe().T
```

Out[10]:

	count	mean	std	min	25%	50%	
CRIM	490.0	3.643241	8.722154	0.00632	0.082045	0.24751	3.647422
ZN	490.0	11.112245	22.844626	0.00000	0.000000	0.00000	12.5
INDUS	490.0	11.113143	6.821302	0.74000	5.190000	9.69000	18.100000
CHAS	490.0	0.059184	0.236209	0.00000	0.000000	0.00000	0.0
NOX	490.0	0.554307	0.116688	0.38500	0.449000	0.53800	0.624000
RM	490.0	6.245471	0.653147	3.56100	5.881000	6.18500	6.5
AGE	490.0	68.278980	28.164790	2.90000	44.550000	76.80000	93.875000
DIS	490.0	3.834519	2.109948	1.13700	2.111050	3.27590	5.2
RAD	490.0	9.514286	8.691297	1.00000	4.000000	5.00000	24.000000
TAX	490.0	408.002041	168.065190	187.00000	280.250000	330.00000	666.0
PTRATIO	490.0	18.520000	2.110478	12.60000	17.400000	19.10000	20.200000
B	490.0	355.855449	92.634273	0.32000	375.912500	391.77000	396.3
LSTAT	490.0	12.924020	7.083180	1.98000	7.347500	11.67500	17.117500
MEDV	490.0	21.635918	7.865301	5.00000	16.700000	20.90000	24.6

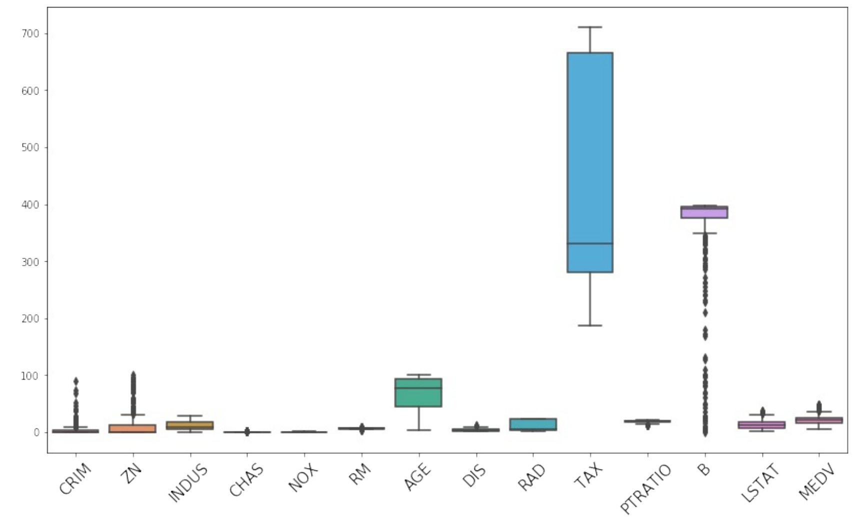
In [11]:

```
df.hist(edgecolor = 'black', linewidth = 1.2, figsize=(20,15)
)
plt.show()
```



In [12]:

```
plt.figure(figsize=(14,8))
sns.boxplot(data = df)
plt.xticks(rotation=45, fontsize=15)
plt.show()
```

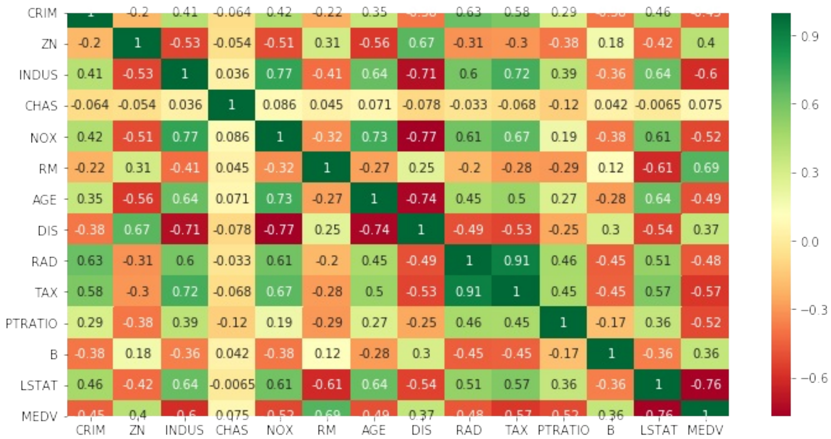


Feature Selection

Using Correlation Matrix

In [13]:

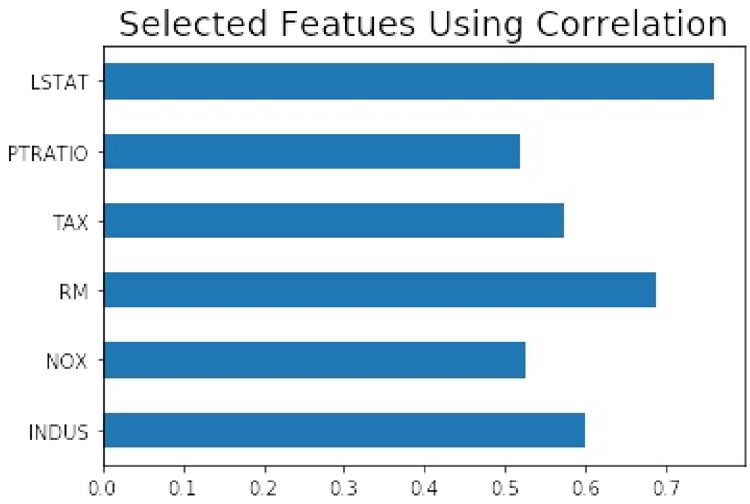
```
plt.figure(figsize=(12,6))
sns.heatmap(df.corr(), annot=True, cmap='RdYlGn')
plt.show()
```



Selecting Highly Correlated Features

In [14]:

```
correlation = df.corr()
corr = abs(correlation['MEDV'])
target_features = corr[corr > 0.5]
target_features.drop('MEDV', inplace=True)
target_features.plot(kind = 'barh')
plt.title('Selected Featues Using Correlation', fontsize=18)
plt.show()
```



Using Lasso Regression

In [15]:

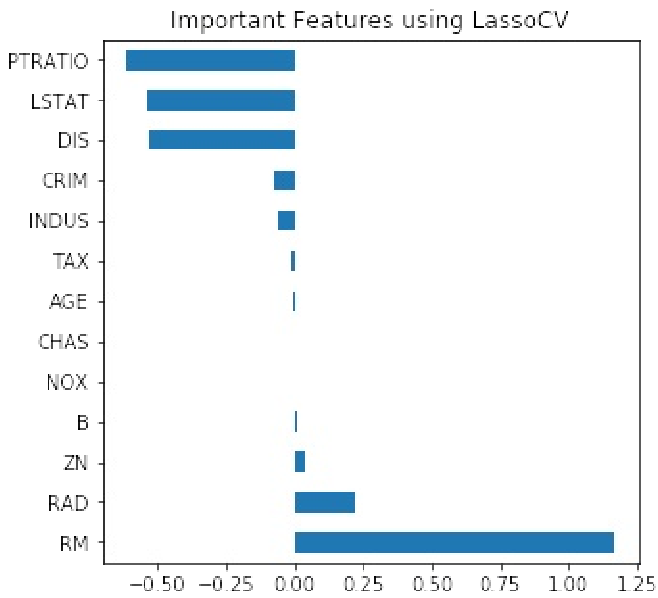
```
from sklearn.linear_model import LassoCV
model = LassoCV(cv=5)
model.fit(X, y)
print(f'Best Alpha using LassoCV: %f' % model.alpha_)
print(f'Best Score using LassoCV: %f' % model.score(X, y))
coef = pd.Series(model.coef_, index=X.columns)

print(f'Lasso Picked {str(sum(coef != 0))} featres and remove
d other {str(sum(coef == 0))} featres')
```

```
Best Alpha using LassoCV: 0.755157
Best Score using LassoCV: 0.730376
Lasso Picked 11 featres and removed other 2 f
eatres
```

In [16]:

```
imp_features = coef.sort_values(ascending=False)
plt.figure(figsize=(5,5))
imp_features.plot(kind= 'barh')
```

```
plt.title('Important Features using LassoCV')
plt.show()
```



Train Test Split

In [17]:

```
X = df[['RM', 'LSTAT', 'PTRATIO', 'INDUS', 'NOX', 'TAX', 'AGE
', 'CRIM']]
y = df['MEDV']
X_train, X_test, y_train, y_test = train_test_split(X, y, tes
t_size = 0.3, random_state = 42)
```

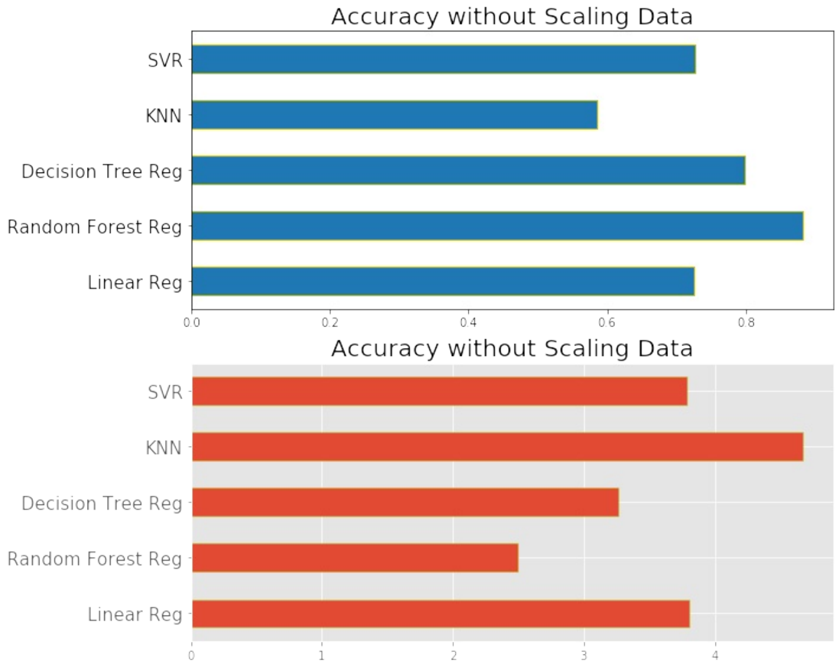
Checking Accuracy for Different Models

Without Scaling Data

In [18]:

```
accuracy = []
rmse = []
models = pd.Series([LinearRegression(), RandomForestRegressor
(n_estimators=100), DecisionTreeRegressor(),
                    KNeighborsRegressor(n_neighbors=3), SVR(k
ernel='linear', gamma='auto')])
regression = pd.Series(['Linear Reg', 'Random Forest Reg', 'D
ecision Tree Reg', 'KNN', 'SVR'])
for i in models:
    model = i
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    accuracy.append(model.score(X_test, y_test))
    rmse.append(np.sqrt(metrics.mean_squared_error(y_test, y_
pred)))
d = {'Accuracy': accuracy, 'RMSE' : rmse}
a = pd.DataFrame(d, index=regression)
plt.figure(figsize=(10,8))
plt.subplot(2,1,1)
a['Accuracy'].plot(kind = 'barh', edgecolor = 'y')
plt.style.use('ggplot')
plt.title('Accuracy without Scaling Data', fontsize = 20)
plt.yticks(fontsize=15)
plt.subplot(2,1,2)
a['RMSE'].plot(kind = 'barh', edgecolor = 'y')
plt.style.use('ggplot')
```

```
plt.title('Accuracy without Scaling Data', fontsize = 20)
plt.yticks(fontsize=15)
plt.tight_layout(h_pad=0.8)
plt.show()
```



Using Scaled Data

In [19]:

```
scaler = MinMaxScaler()
X_scaled = scaler.fit_transform(X)
X_train, X_test, y_train, y_test = train_test_split(X_scaled,
 y, test_size=0.3, random_state=42)
accuracy = []
rmse = []
models = pd.Series([LinearRegression(), RandomForestRegressor
(n_estimators=100), DecisionTreeRegressor(),
                    KNeighborsRegressor(n_neighbors=3), SVR(k
ernel='linear', gamma='auto')])
regression = pd.Series(['Linear Reg', 'Random Forest Reg', 'D
```

```
ecision Tree Reg', 'KNN', 'SVR'])
for i in models:
    model = i
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    accuracy.append(model.score(X_test, y_test))
    rmse.append(np.sqrt(metrics.mean_squared_error(y_test, y_
pred)))
d = {'Accuracy': accuracy, 'RMSE' : rmse}
a = pd.DataFrame(d, index=regression)
# print(a)
plt.figure(figsize=(10,8))
plt.subplot(2,1,1)
a['Accuracy'].plot(kind = 'barh')
plt.title('Accuracy with Scaled Data', fontsize= 20)
plt.yticks(fontsize=15)
plt.subplot(2,1,2)
a['RMSE'].plot(kind = 'barh')
plt.title('RMSe with Scaled Data', fontsize= 20)
plt.yticks(fontsize=15)
plt.tight_layout(h_pad=0.8)
plt.show()
```

Resacling and Normalizing Data in Pipeline

In [20]:

```
steps = [('scaler', StandardScaler()), ('RFR', RandomForestRe
gressor(n_estimators=100))]
pipeline = Pipeline(steps)
pipeline.fit(X_train, y_train)
# y_pred = pipeline.predict(X_test)
# print(pipeline.score(X_test, y_test))
```

Out[20]:

```
Pipeline(memory=None,
         steps=[('scaler',
                 StandardScaler(copy=True, wi
th_mean=True, with_std=True)),
                ('RFR',
                 RandomForestRegressor(bootst
rap=True, criterion='mse',
                                       max_de
pth=None, max_features='auto',
                                       max_le
af_nodes=None,
                                       min_im
purity_decrease=0.0,
                                       min_im
purity_split=None,
                                       min_sa
mples_leaf=1, min_samples_split=2,
                                       min_we
ight_fraction_leaf=0.0,
                                       n_esti
mators=100, n_jobs=None,
```

```
                                                   oob_sc
ore=False, random_state=None,
                                                   verbos
e=0, warm_start=False))],
         verbose=False)
```

Saving Model

In [21]:

```
from joblib import dump, load
dump(pipeline, 'price_pred_model.pkl')
a = load('price_pred_model.pkl')
print(a.score(X_test, y_test))
```

```
0.8787411558595517
```