# assignment8

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# 2 Course: M.Sc. Data Science

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# 5 Subject: Fundatmental of Data Science

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[78]:
```
import pandas as pd
import numpy as np

from sklearn.model_selection import train_test_split
from sklearn.linear_model import Ridge,Lasso,LinearRegression
from sklearn.metrics import mean_squared_error as mse
import seaborn as sns

import matplotlib.pyplot as plt
```

[79]:
```
data=pd.read_csv('BostonHousing.csv')
```

[80]:
```
data.head()
```

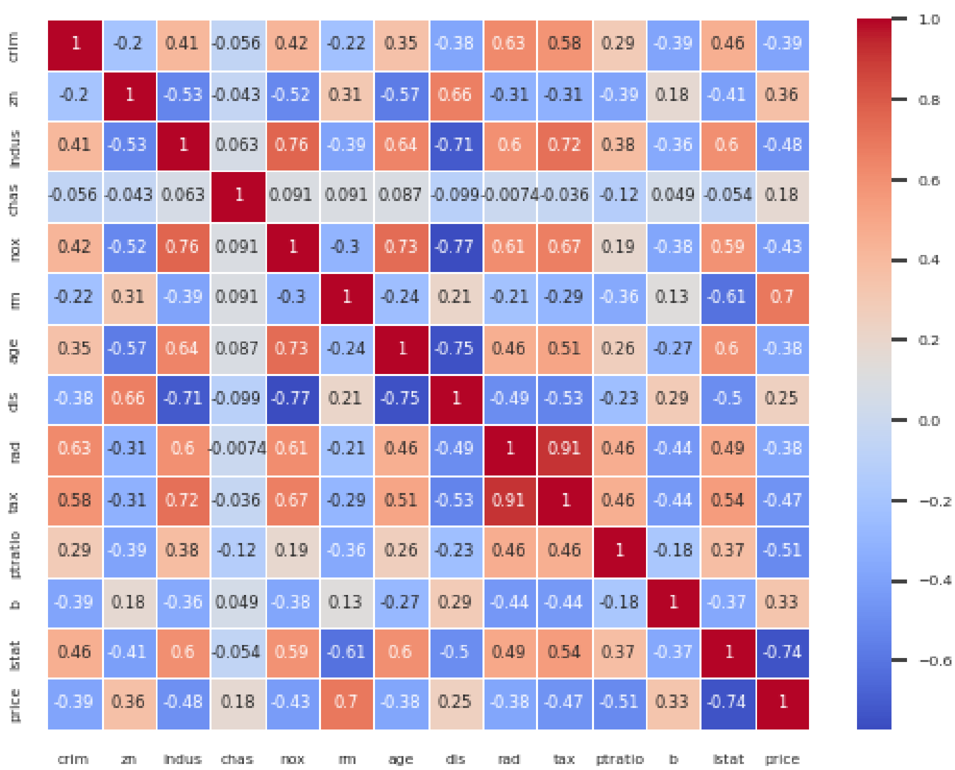
[80]:
```
      crim    zn  indus  chas    nox     rm   age     dis  rad  tax  ptratio  \
0  0.00632  18.0   2.31     0  0.538  6.575  65.2  4.0900    1  296     15.3
1  0.02731   0.0   7.07     0  0.469  6.421  78.9  4.9671    2  242     17.8
2  0.02729   0.0   7.07     0  0.469  7.185  61.1  4.9671    2  242     17.8
3  0.03237   0.0   2.18     0  0.458  6.998  45.8  6.0622    3  222     18.7
4  0.06905   0.0   2.18     0  0.458  7.147  54.2  6.0622    3  222     18.7

        b  lstat  price
0  396.90   4.98   24.0
1  396.90   9.14   21.6
2  392.83   4.03   34.7
3  394.63   2.94   33.4
4  396.90   5.33   36.2
```

### 12.0.1 Construct the correlation heat map for all the variables. What do you observe?

[81]:
```
corr=data.corr()
```

[106]:
```
sns.set(font_scale=0.5)
sns.heatmap(corr,cmap='coolwarm',annot=True,linewidths=0.5)
```

[106]: <Axes: >



#### 12.0.2 Divide the data such that 75% data is train and remaining is test.

[83]:
```
independent_vars=data[data.columns[:-1]]
price=data['price']
r_data=np.array(independent_vars).reshape(independent_vars.shape)
r_price=np.array(price).reshape(-1,1)
```

[84]:
```
train_data,test_data,train_price,test_price=train_test_split(r_data,r_price,train_size=0.
↪75,random_state=1)
```

#### 12.0.3 Fit multiple linear regression model, ridge regression and lasso regression with ( = 1), the tuning parameter on the train data.

[85]:
```
linear_model=LinearRegression()
ridge_model=Ridge(alpha=1)
lasso_model=Lasso(alpha=1)
```

[86]:
```
linear_model.fit(train_data,train_price)
ridge_model.fit(train_data,train_price)
lasso_model.fit(train_data,train_price)
```

[86]:
```
Lasso(alpha=1)
```

#### 12.0.4 Extract the estimated coefficient values for each model with respect to the independent variables as output. What are the changes you observe in the coefficient values?

[87]:
```
coef_for_linear=linear_model.coef_[0]
print(f'coefficients: {coef_for_linear}\nintercept: {linear_model.intercept_}')
```

```
coefficients: [-1.14428903e-01  5.71299780e-02  3.83002824e-02  2.42854641e+00
 -2.12326236e+01  2.87723416e+00  6.91118094e-03 -1.47158266e+00
  3.05784197e-01 -1.06750361e-02 -9.96138270e-01  6.27746234e-03
 -5.57414427e-01]
intercept: [45.19251539]
```

[88]:
```
coef_for_ridge=ridge_model.coef_[0]
print(f'coefficients: {coef_for_ridge}\nintercept: {ridge_model.intercept_}')
```

```
coefficients: [-1.09313326e-01  5.81466109e-02 -6.57912472e-03  2.17625586e+00
 -1.14648161e+01  2.96948364e+00 -1.23491124e-03 -1.33558053e+00
  2.86708621e-01 -1.17634405e-02 -8.80356116e-01  6.85811788e-03
 -5.68412252e-01]
intercept: [38.1537646]
```

[89]:
```
coef_for_lasso=lasso_model.coef_
print(f'coefficients: {coef_for_lasso}\nintercept: {lasso_model.intercept_}')
```

```
coefficients: [-0.06878405  0.05536254 -0.          0.         -0.          0.
  0.02336436 -0.54610017  0.24646698 -0.01288932 -0.73552217  0.00590525
 -0.79338245]
intercept: [47.06409184]
```

observation: Coefficent values in Lasso regression are tending to zero

#### 12.0.5 Use the fitted models on the test data to predict price and compute the MSE for each model. Which model gives the best prediction?

[90]:
```
pred_for_linear=linear_model.predict(test_data)
pred_for_ridge=ridge_model.predict(test_data)
pred_for_lasso=lasso_model.predict(test_data)
```

[91]:
```
mse_for_linear=mse(test_price,pred_for_linear)
mse_for_ridge=mse(test_price,pred_for_ridge)
mse_for_lasso=mse(test_price,pred_for_lasso)
```

[92]:
```
print(f'MSE for Linear Regression: {mse_for_linear}\nMSE for Ridge Regression:␣
↪{mse_for_ridge}\nMSE for Lasso Regression: {mse_for_lasso}')
```

```
MSE for Linear Regression: 21.89776539604947
MSE for Ridge Regression: 21.319619091968626
MSE for Lasso Regression: 33.46214285179805
```

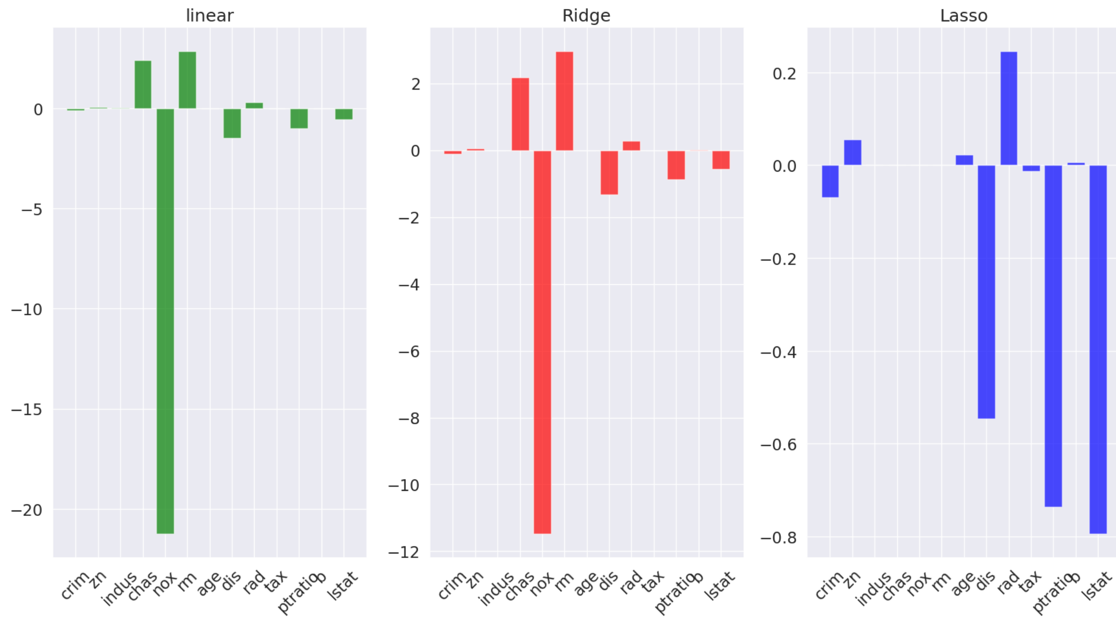
observation: Ridge linear regression has the least MSE, hence ridge model gives best predictions

#### 12.0.6 Create three adjacent barplots with respect to each estimated coefficient value corresponding to each independent variable. Use green, red and blue respectively for linear, ridge and lasso.

[93]:
```
independent_names=[i for i in data.columns if i!='price']
```

[95]:
```
sns.set(font_scale=1.5)
fig,axes=plt.subplots(nrows=1,ncols=3,figsize=(20,10))

axes[0].bar(independent_names,coef_for_linear,color='green',alpha=0.7)
axes[0].set_title('linear')
axes[0].tick_params(axis='x',rotation=45)
axes[1].bar(independent_names,coef_for_ridge,color='red',alpha=0.7)
axes[1].set_title('Ridge')
axes[1].tick_params(axis='x',rotation=45)

axes[2].bar(independent_names,coef_for_lasso,color='blue',alpha=0.7)
axes[2].set_title('Lasso')
```

```
axes[2].tick_params(axis='x',rotation=45)
plt.show()
```




### 12.0.7 Is lasso eliminating the correlated variables?

Yes Lasso regression has made coeffient value of ['chas', 'indus', 'nox' and 'rm'] zero, hence eliminated them.

[ ]:

```

```