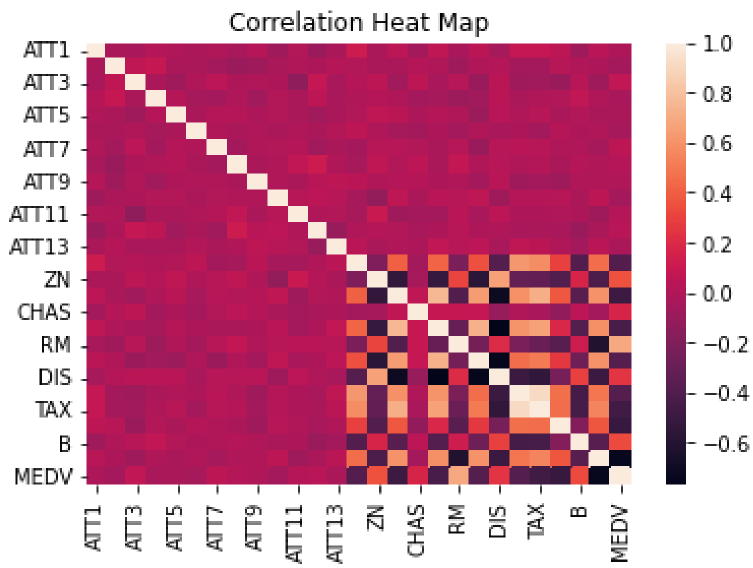
Emma Mayes (eemayes2)

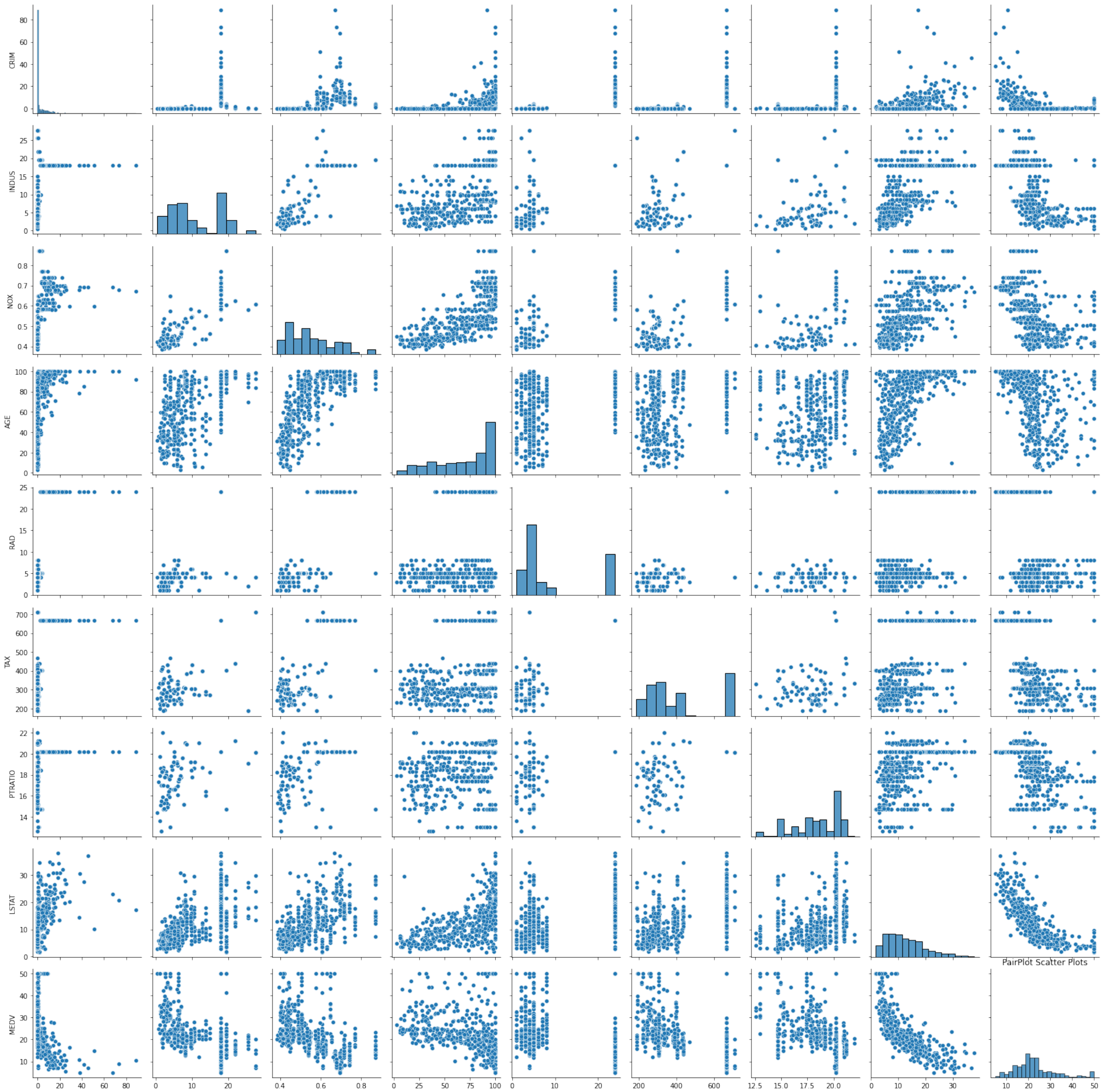
IE516 MLF F21

Module 4 Homework (Regression)

Part 1: Exploratory Data Analysis

Describe the data sufficiently using the methods and visualizations that we used previously in Module 3 and again this week. Include any output, graphs, tables, heatmaps, box plots, etc. Label your figures and axes. DO NOT INCLUDE CODE!





(Refer to Colab Notebook for a bigger/scrollable image)

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	MEDV
count	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000
mean	3.613524	11.363636	11.136779	0.069170	0.554695	6.284634	68.574901	3.795043	9.549407	408.237154	18.455534	356.674032	12.653063	22.532806
std	8.601545	23.322453	6.860353	0.253994	0.115878	0.702617	28.148861	2.105710	8.707259	168.537116	2.164946	91.294864	7.141062	9.197104
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000	2.900000	1.129600	1.000000	187.000000	12.600000	0.320000	1.730000	5.000000
25%	0.082045	0.000000	5.190000	0.000000	0.449000	5.885500	45.025000	2.100175	4.000000	279.000000	17.400000	375.377500	6.950000	17.025000
50%	0.256510	0.000000	9.690000	0.000000	0.538000	6.208500	77.500000	3.207450	5.000000	330.000000	19.050000	391.440000	11.360000	21.200000
75%	3.677082	12.500000	18.100000	0.000000	0.624000	6.623500	94.075000	5.188425	24.000000	666.000000	20.200000	396.225000	16.955000	25.000000
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000	12.126500	24.000000	711.000000	22.000000	396.900000	37.970000	50.000000

Split data into training and test sets. Use random_state = 42. Use 80% of the data for the training set. Use the same split for all models.

Part 2: Linear regression

Fit a linear model using SKlearn to all of the features of the dataset. Describe the model (coefficients and y intercept), plot the residual errors, calculate performance metrics: MSE and R2.

See code PDF at the end.

Part 3.1: Ridge regression

Fit a Ridge model using SKlearn to all of the features of the dataset. Test some settings for alpha. Describe the model (coefficients and y intercept), plot the residual errors, calculate performance metrics: MSE and R2. Which alpha gives the best performing model?

When tested, alpha = 0.1 gave the best performing model. See code PDF at the end for more.

Part 3.2: LASSO regression

Fit a LASSO model using SKlearn to all of the features of the dataset. Test some settings for alpha. Describe the model (coefficients and y intercept), plot the residual errors, calculate performance metrics: MSE and R2. Which alpha gives the best performing model?

When tested, alpha = 0.3 gave the best performing model. See code PDF at the end for more.

Part 4: Conclusions

When testing all three types of regression, weirdly enough, Linear Regression gave the best results, with Ridge being a close second in performance. While I'm not sure it truly gives the best results because it includes all the noise variables, there must have been enough correlation with the noise and actual variables that it somehow worked. Instead of fitting a linear model on all features of the dataset as the instructions had asked, a better comparison across model types would have been to include those most-correlated features with the target variable. My LASSO model was built to drop these out on their own, which was done correctly for the best alpha parameter, but did not have the best performance either.

Part 5: Appendix

GitHub Repo: https://github.com/eemayes2/IE517_F21_HW4

IE517_HWK4

September 17, 2021

The linear model fit on all the variables should have a high R2 and a somewhat large MSE on the in-sample test, but perform less well on the out-of-sample test due to overfitting. Hopefully Lasso and Ridge will remedy that, although the effect may be hard to see with just a single test-train split.

[76]:
```
#Import libraries needed
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')

#Check if any null values we need to change
def num_missing(x):
    return sum(x.isnull())
```

[9]:
```
#Read in Data
df = pd.read_csv('housing2(2).csv', header=0)
#Reminder: ATT1-13 is noise, MEDV is target variable
df.head()
```

[9]:
```
       ATT1      ATT2      ATT3      ATT4  ...  PTRATIO       B  LSTAT  MEDV
0  0.038327  0.592379  0.655174  0.119839  ...     15.3  396.90   4.98  24.0
1  0.225022  0.983103  0.803619  0.836315  ...     17.8  396.90   9.14  21.6
2  0.423233  0.375808  0.271293  0.729824  ...     17.8  392.83   4.03  34.7
3  0.743370  0.929103  0.589894  0.644012  ...     18.7  394.63   2.94  33.4
4  0.378623  0.786609  0.712752  0.110274  ...     18.7  396.90   5.33  36.2

[5 rows x 27 columns]
```

[10]:
```
print(df.apply(num_missing, axis = 0))
```

```
ATT1       0
ATT2       0
ATT3       0
ATT4       0
ATT5       0
ATT6       0
```

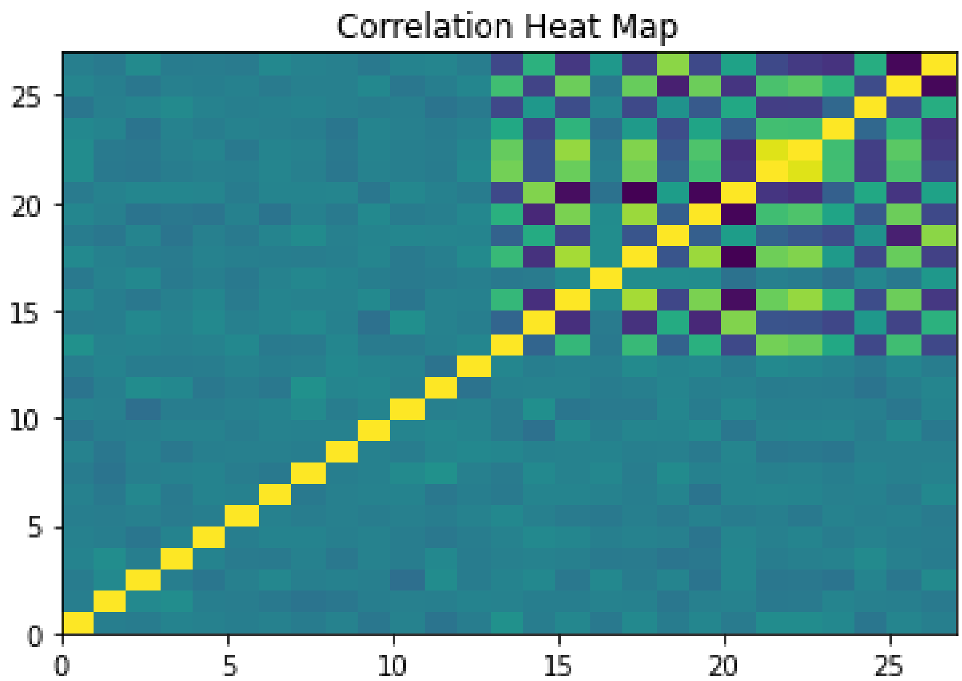
```
ATT7       0
ATT8       0
ATT9       0
ATT10      0
ATT11      0
ATT12      0
ATT13      0
CRIM       0
ZN         0
INDUS      0
CHAS       0
NOX        0
RM         0
AGE        0
DIS        0
RAD        0
TAX        0
PTRATIO    0
B          0
LSTAT      0
MEDV       0
dtype: int64
```

0.1 Part 1: Exploratory Data Analysis

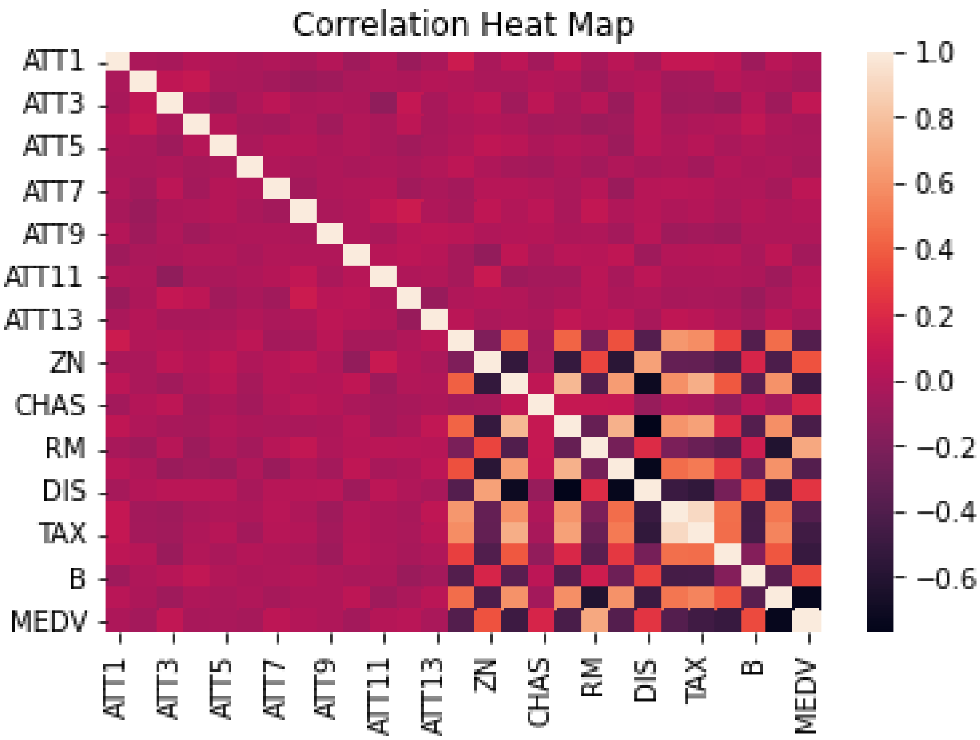
[114]:
```python
df.iloc[:, 13:].describe()
```

[114]:
```
             CRIM          ZN       INDUS  ...           B       LSTAT
MEDV
count  506.000000  506.000000  506.000000  ...  506.000000  506.000000
506.000000
mean     3.613524   11.363636   11.136779  ...  356.674032   12.653063
22.532806
std      8.601545   23.322453    6.860353  ...   91.294864    7.141062
9.197104
min      0.006320    0.000000    0.460000  ...    0.320000    1.730000
5.000000
25%      0.082045    0.000000    5.190000  ...  375.377500    6.950000
17.025000
50%      0.256510    0.000000    9.690000  ...  391.440000   11.360000
21.200000
75%      3.677082   12.500000   18.100000  ...  396.225000   16.955000
25.000000
max     88.976200  100.000000   27.740000  ...  396.900000   37.970000
50.000000

[8 rows x 14 columns]
```

[16]:
```
corMat = pd.DataFrame(df.corr())

plt.pcolor(corMat)
plt.title("Correlation Heat Map")
plt.show()
```

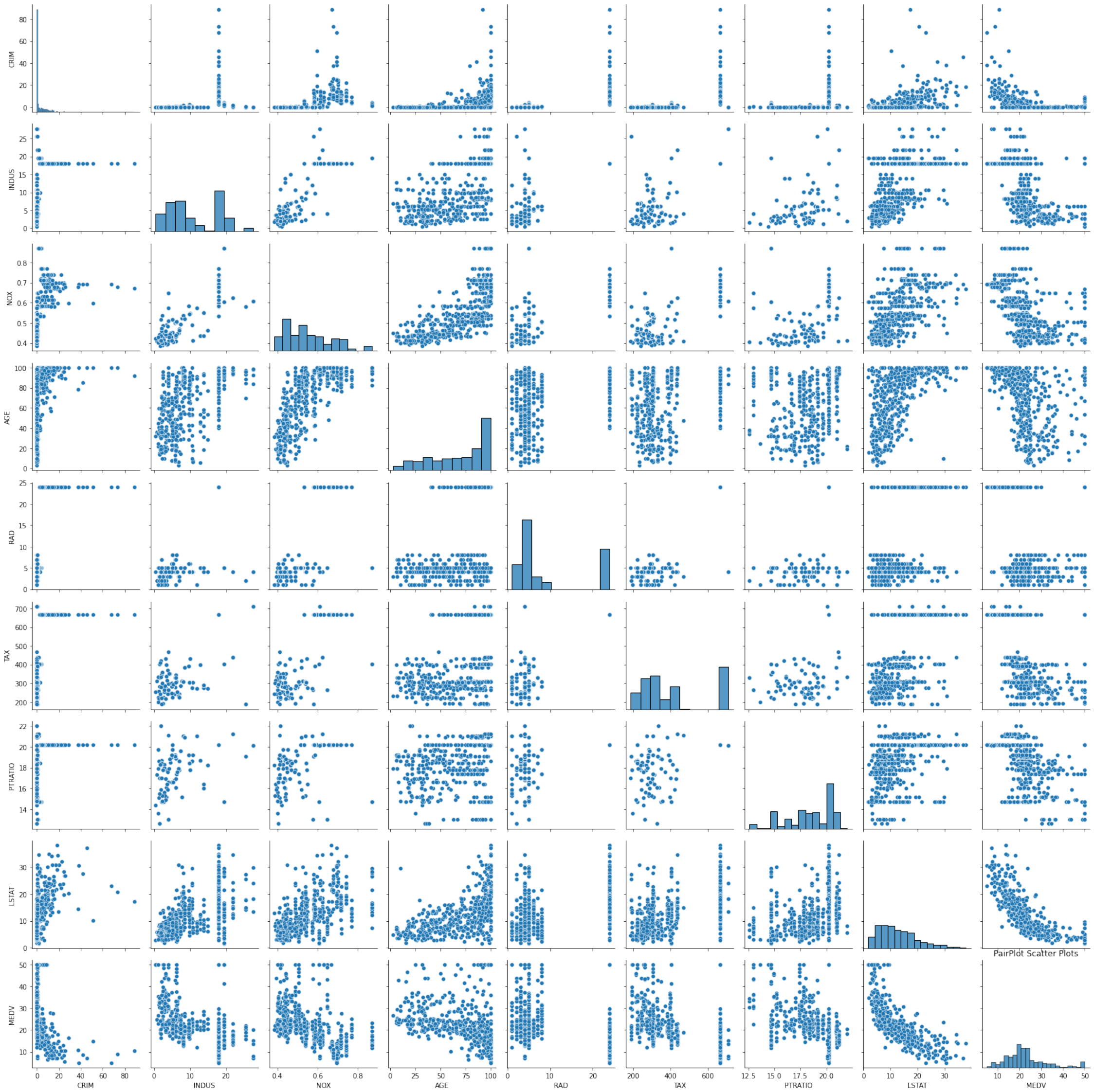


[20]:
```
correlation_mat = df.corr()

sns.heatmap(correlation_mat, annot = False)
plt.title("Correlation Heat Map")
plt.show()
```



[21]:
```
#Use cols most correlated with MEDV
cols = ['CRIM', 'INDUS', 'NOX','AGE', 'RAD', 'TAX', 'PTRATIO', 'LSTAT', 'MEDV']
sns.pairplot(df[cols], size = 2.5)
plt.tight_layout()
plt.title("PairPlot Scatter Plots")
plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/axisgrid.py:2076: UserWarning:
The `size` parameter has been renamed to `height`; please update your code.
  warnings.warn(msg, UserWarning)
```



[25]:

```
#Split into training-test sets
from sklearn.model_selection import train_test_split

x = df.drop(columns = ['MEDV'])
x.head()

X_train, X_test, y_train, y_test = train_test_split(x, df['MEDV'], test_size=0.20, random_state=42)
```

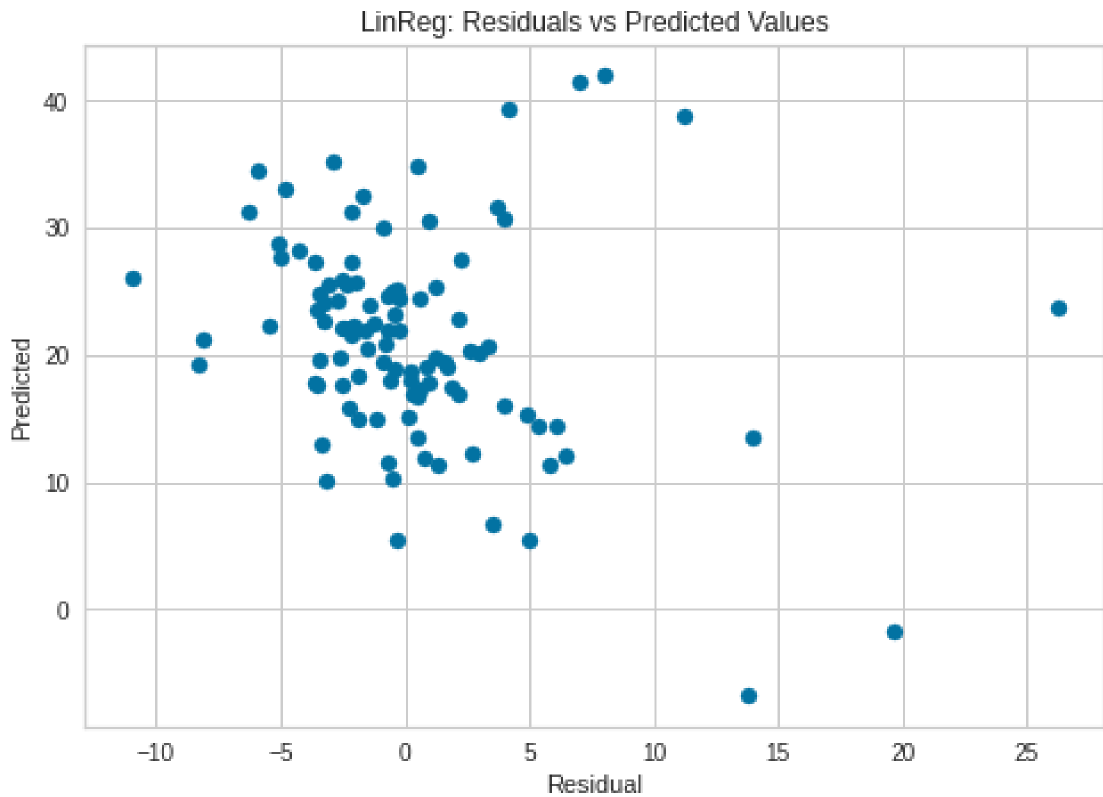
0.2 Part 2: Linear Regression

[52]:
```
from sklearn.linear_model import LinearRegression,RidgeCV, LassoCV
from sklearn.linear_model import Ridge, Lasso
from sklearn.metrics import mean_squared_error, r2_score
```

[146]:
```
lin_reg = LinearRegression()
lreg = lin_reg.fit(X_train, y_train)
y_pred = lreg.predict(X_test)
y_train_pred = lreg.predict(X_train)

print('Intercept = ' + str(lreg.intercept_))
print('Coeffs = ' + str(lreg.coef_))
```

```
Intercept = 29.01184117293093
Coeffs = [ 2.89556912e+00 -2.40286871e-01  5.59299658e-01 -1.05366827e-01
 -7.67931626e-01 -6.19536586e-01  6.66791594e-01 -2.79369230e-01
 -1.41197737e-01 -1.01755261e+00 -9.66242999e-01  4.57906074e-01
 -1.32764058e-01 -1.27945481e-01  3.23592942e-02  4.02659544e-02
  2.74293085e+00 -1.70235838e+01  4.48169721e+00 -6.42849583e-03
 -1.47039413e+00  2.56793051e-01 -1.05131783e-02 -8.92191033e-01
  1.30869818e-02 -5.01078827e-01]
```

[147]:
```
residuals = y_test-y_pred
plt.scatter(residuals,y_pred)
plt.xlabel("Residual")
plt.ylabel("Predicted")
plt.title("LinReg: Residuals vs Predicted Values")
plt.show()
```



[148]:
```
print("Train Score: " + str(lreg.score(X_train, y_train)))
print("Test Score: " + str(lreg.score(X_test, y_test)))
print("Mean Squared Error (MSE): " + str(mean_squared_error(y_test, y_pred)))

print("Train R^2: " + str(r2_score(y_train, y_train_pred)))
print("Test R^2: " + str(r2_score(y_test, y_pred)))
```

```
Train Score: 0.762725461446246
Test Score: 0.6368627208821082
Mean Squared Error (MSE): 26.630230484261155
Train R^2: 0.762725461446246
Test R^2: 0.6368627208821082
```

0.3 Part 3.1: Ridge Regression

[138]:
```
import statsmodels.api as sm
parameters = [1e-25, 1e-15, 1e-10, 1e-8, 1e-4, 1e-3, 1e-2, 0.05, 0.1, 0.15, 0.
↪2, 0.25, 0.3, 0.5, 0.75, 1, 1.5, 2, 2.5, 3, 3.5, 4, 4.5, 5, 10, 20, 30]

ridge = RidgeCV(alphas = parameters, scoring = 'r2')

rreg = ridge.fit(X_train, y_train)
```

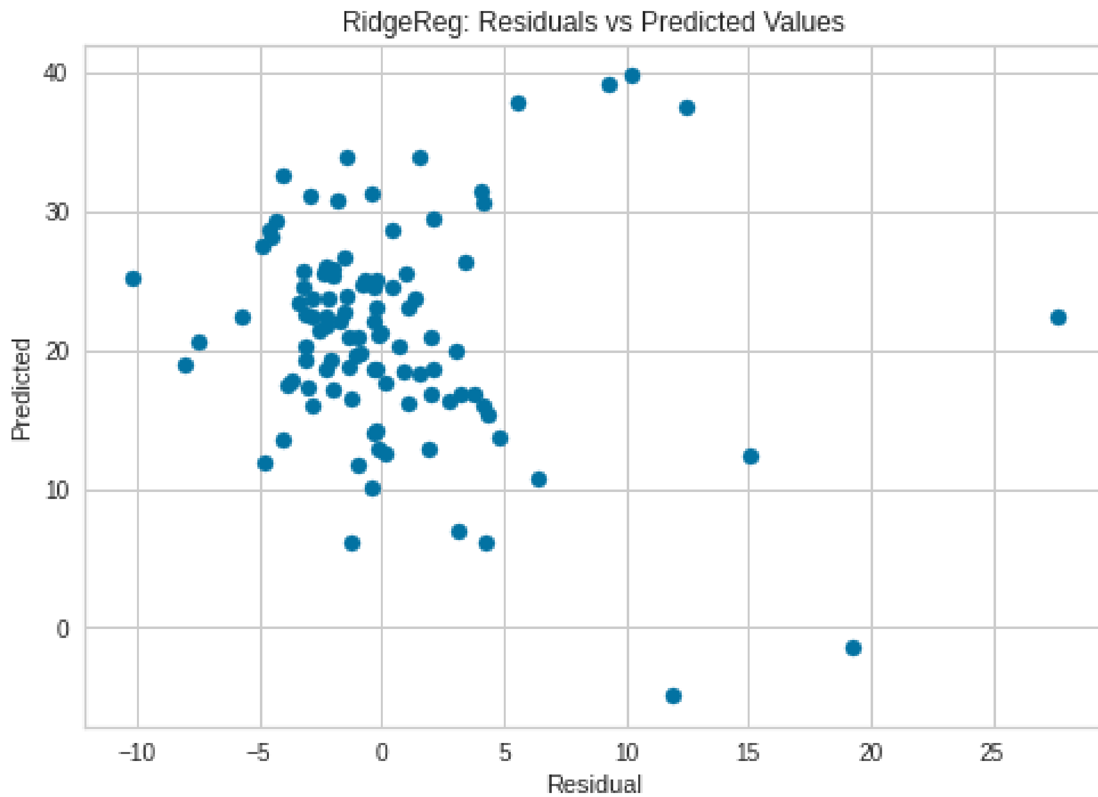
```python
print(rreg.get_params)
print('Best alpha: ' + str(rreg.alpha_))
```

```
<bound method BaseEstimator.get_params of RidgeCV(alphas=array([1.0e-25,
1.0e-15, 1.0e-10, 1.0e-08, 1.0e-04, 1.0e-03, 1.0e-02,
       5.0e-02, 1.0e-01, 1.5e-01, 2.0e-01, 2.5e-01, 3.0e-01, 5.0e-01,
       7.5e-01, 1.0e+00, 1.5e+00, 2.0e+00, 2.5e+00, 3.0e+00, 3.5e+00,
       4.0e+00, 4.5e+00, 5.0e+00, 1.0e+01, 2.0e+01, 3.0e+01]),
        cv=None, fit_intercept=True, gcv_mode=None, normalize=False,
        scoring='r2', store_cv_values=False)>
Best alpha: 0.1
```

[139]:
```python
ridge_best = Ridge(alpha = rreg.alpha_, normalize = True)
ridge_best.fit(X_train, y_train)



y_pred = ridge_best.predict(X_test)
y_train_pred = ridge_best.predict(X_train)

print('Intercept = ' + str(ridge_best.intercept_))
print('Coeffs = ' + str(ridge_best.coef_))
```

```
Intercept = 21.23009987843051
Coeffs = [ 2.53775000e+00 -4.66969023e-01  4.57586547e-01 -1.77850645e-01
 -8.57166974e-01 -4.78641461e-01  7.39065961e-01 -3.04098221e-01
 -2.21596848e-01 -9.66175457e-01 -7.89347361e-01  4.26814409e-01
 -2.34582768e-01 -9.96982632e-02  1.67992880e-02 -2.38166384e-02
  2.98945287e+00 -1.04456466e+01  4.50145609e+00 -6.44787859e-03
 -1.00226582e+00  9.95772909e-02 -4.27301453e-03 -7.82132603e-01
  1.19616595e-02 -4.49305383e-01]
```

[140]:
```python
residuals = y_test-y_pred
plt.scatter(residuals,y_pred)
plt.xlabel("Residual")
plt.ylabel("Predicted")
plt.title("RidgeReg: Residuals vs Predicted Values")
plt.show()
```



[141]:
```
print("Train Score: " + str(ridge_best.score(X_train, y_train)))
print("Test Score: " + str(ridge_best.score(X_test, y_test)))

print("Mean Squared Error (MSE): " + str(mean_squared_error(y_test, y_pred)))

print("Train R^2: " + str(r2_score(y_train, y_train_pred)))
print("Test R^2: " + str(r2_score(y_test, y_pred)))
```

```
Train Score: 0.754734471040975
Test Score: 0.6339582689284009
Mean Squared Error (MSE): 26.843224934033902
Train R^2: 0.754734471040975
Test R^2: 0.6339582689284009
```

Part 3.2: LASSO Regression

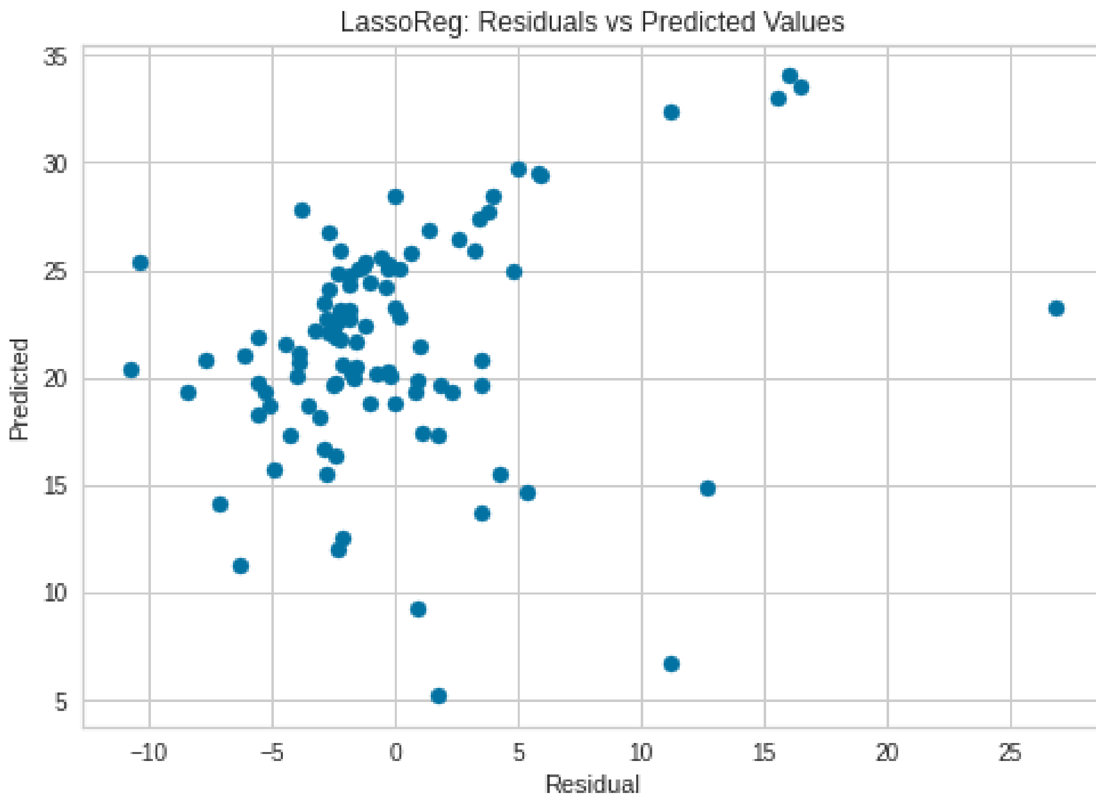
[142]:
```
#find best alpha
lasso_regressor = LassoCV(alphas = parameters).fit(X_train, y_train)

print(lasso_regressor.get_params)
print(lasso_regressor.alpha_)
```

```
<bound method BaseEstimator.get_params of LassoCV(alphas=[1e-25, 1e-15, 1e-10,
1e-08, 0.0001, 0.001, 0.01, 0.05, 0.1,
                0.15, 0.2, 0.25, 0.3, 0.5, 0.75, 1, 1.5, 2, 2.5, 3, 3.5, 4, 4.5,
                5, 10, 20, 30],
        copy_X=True, cv=None, eps=0.001, fit_intercept=True, max_iter=1000,
        n_alphas=100, n_jobs=None, normalize=False, positive=False,
        precompute='auto', random_state=None, selection='cyclic', tol=0.0001,
        verbose=False)>
0.1
```

[143]:
```
lass_best = Lasso(alpha = lasso_regressor.alpha_, normalize = True)
lass_best.fit(X_train, y_train)

y_pred = lass_best.predict(X_test)
y_train_pred = lass_best.predict(X_train)

print('Intercept = ' + str(lass_best.intercept_))
print('Coeffs = ' + str(lass_best.coef_))
```

```
Intercept = 10.719938826593024
Coeffs = [ 0.          -0.          0.          -0.          -0.          -0.
  0.          0.          -0.          -0.          -0.          -0.
 -0.          -0.          0.          -0.          0.          -0.
  3.54335167 -0.          0.          -0.          -0.          -0.26526595
  0.          -0.43697906]
```

[144]:
```
residuals = y_test-y_pred
plt.scatter(residuals,y_pred)
plt.xlabel("Residual")
plt.ylabel("Predicted")
plt.title("LassoReg: Residuals vs Predicted Values")
plt.show()
```



[145]:
```
print("Train Score: " + str(lass_best.score(X_train, y_train)))
print("Test Score: " + str(lass_best.score(X_test, y_test)))

print("Mean Squared Error (MSE): " + str(mean_squared_error(y_test, y_pred)))

print("Train R^2: " + str(r2_score(y_train, y_train_pred)))
print("Test R^2: " + str(r2_score(y_test, y_pred)))
```

```
Train Score: 0.6112945565136205
Test Score: 0.5824911941775328
Mean Squared Error (MSE): 30.617500233710192
Train R^2: 0.6112945565136205
Test R^2: 0.5824911941775328
```

0.4 Integrity Statements

[1]:
```
print("My name is Emma Mayes")
print("My NetID is: eemayes2")
print("I hereby certify that I have read the University policy on Academic␣
↪Integrity and that I am not in violation.")
```

```
My name is Emma Mayes
My NetID is: eemayes2
I hereby certify that I have read the University policy on Academic Integrity
and that I am not in violation.
```

[152]:
```
!wget -nc https://raw.githubusercontent.com/brpy/colab-pdf/master/colab_pdf.py
from colab_pdf import colab_pdf
colab_pdf('IE517_HWK4.ipynb')
```

```
File colab_pdf.py already there; not retrieving.
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
<ipython-input-152-55e29c3c37f7> in <module>()
      1 get_ipython().system('wget -nc https://raw.githubusercontent.com/brpy/colab-pdf/master/colab_pdf.py')
      2 from colab_pdf import colab_pdf
----> 3 colab_pdf('IE517_HWK4.ipynb')


/content/colab_pdf.py in colab_pdf(file_name, notebookpath)
     20     # Check if the notebook exists in the Drive.
     21     if not os.path.isfile(os.path.join(notebookpath, file_name)):
---> 22         raise ValueError(f"file '{file_name}' not found in path '{notebookpath}'.")
     23
     24     # Installing all the recommended packages.


ValueError: file 'IE517_HWK4.ipynb' not found in path '/content/drive/MyDrive/Colab Notebooks/'.
```