In [1]:
```
import numpy as np
import pandas as pd
import scipy.stats as stats
import matplotlib.pyplot as plt
from sklearn.datasets import load_boston
import seaborn as sns
from sklearn.model_selection import train_test_split
from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn.linear_model import Ridge, Lasso, RidgeCV, LassoCV, ElasticNet, E
lasticNetCV, LinearRegression
import statsmodels.formula.api as smf
from sklearn.metrics import mean_squared_error, r2_score
```

In [2]:
```
boston = load_boston()
bos = pd.DataFrame(boston.data, columns=boston.feature_names)
```

In [3]:
```
bos.head()
```

Out[3]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LST
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	396.90	4.
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8	396.90	9.
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8	392.83	4.
3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3.0	222.0	18.7	394.63	2.
4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3.0	222.0	18.7	396.90	5.

In [4]:
```
print(boston.keys())
```

```
dict_keys(['data', 'target', 'feature_names', 'DESCR', 'filename'])
```

In [5]:
```
bos['MEDV'] = boston.target
```

In [6]:
```
bos.head()
```

Out[6]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LST
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	396.90	4.
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8	396.90	9.
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8	392.83	4.
3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3.0	222.0	18.7	394.63	2.
4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3.0	222.0	18.7	396.90	5.

In [7]:
```
bos.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
```

There are no missing values

In [8]:
```
print(boston.DESCR)
```

```
.. _boston_dataset:

Boston house prices dataset
---------------------------

**Data Set Characteristics:**

    :Number of Instances: 506

    :Number of Attributes: 13 numeric/categorical predictive. Median Value (a
ttribute 14) is usually the target.

    :Attribute Information (in order):
        - CRIM     per capita crime rate by town
        - ZN       proportion of residential land zoned for lots over 25,000
sq.ft.
        - INDUS    proportion of non-retail business acres per town
        - CHAS     Charles River dummy variable (= 1 if tract bounds river; 0
otherwise)
        - NOX      nitric oxides concentration (parts per 10 million)
        - RM       average number of rooms per dwelling
        - AGE      proportion of owner-occupied units built prior to 1940
        - DIS      weighted distances to five Boston employment centres
        - RAD      index of accessibility to radial highways
        - TAX      full-value property-tax rate per $10,000
        - PTRATIO  pupil-teacher ratio by town
        - B        1000(Bk - 0.63)^2 where Bk is the proportion of blacks by
town
        - LSTAT    % lower status of the population
        - MEDV     Median value of owner-occupied homes in $1000's

    :Missing Attribute Values: None

    :Creator: Harrison, D. and Rubinfeld, D.L.

This is a copy of UCI ML housing dataset.
https://archive.ics.uci.edu/ml/machine-learning-databases/housing/


This dataset was taken from the StatLib library which is maintained at Carneg
ie Mellon University.

The Boston house-price data of Harrison, D. and Rubinfeld, D.L. 'Hedonic
prices and the demand for clean air', J. Environ. Economics & Management,
vol.5, 81-102, 1978.   Used in Belsley, Kuh & Welsch, 'Regression diagnostics
...', Wiley, 1980.   N.B. Various transformations are used in the table on
pages 244-261 of the latter.

The Boston house-price data has been used in many machine learning papers tha
t address regression
problems.

.. topic:: References

   - Belsley, Kuh & Welsch, 'Regression diagnostics: Identifying Influential
Data and Sources of Collinearity', Wiley, 1980. 244-261.
   - Quinlan,R. (1993). Combining Instance-Based and Model-Based Learning. In
```

```
Proceedings on the Tenth International Conference of Machine Learning, 236-24
3, University of Massachusetts, Amherst. Morgan Kaufmann.
```

In [9]:
```
bos.describe()
```

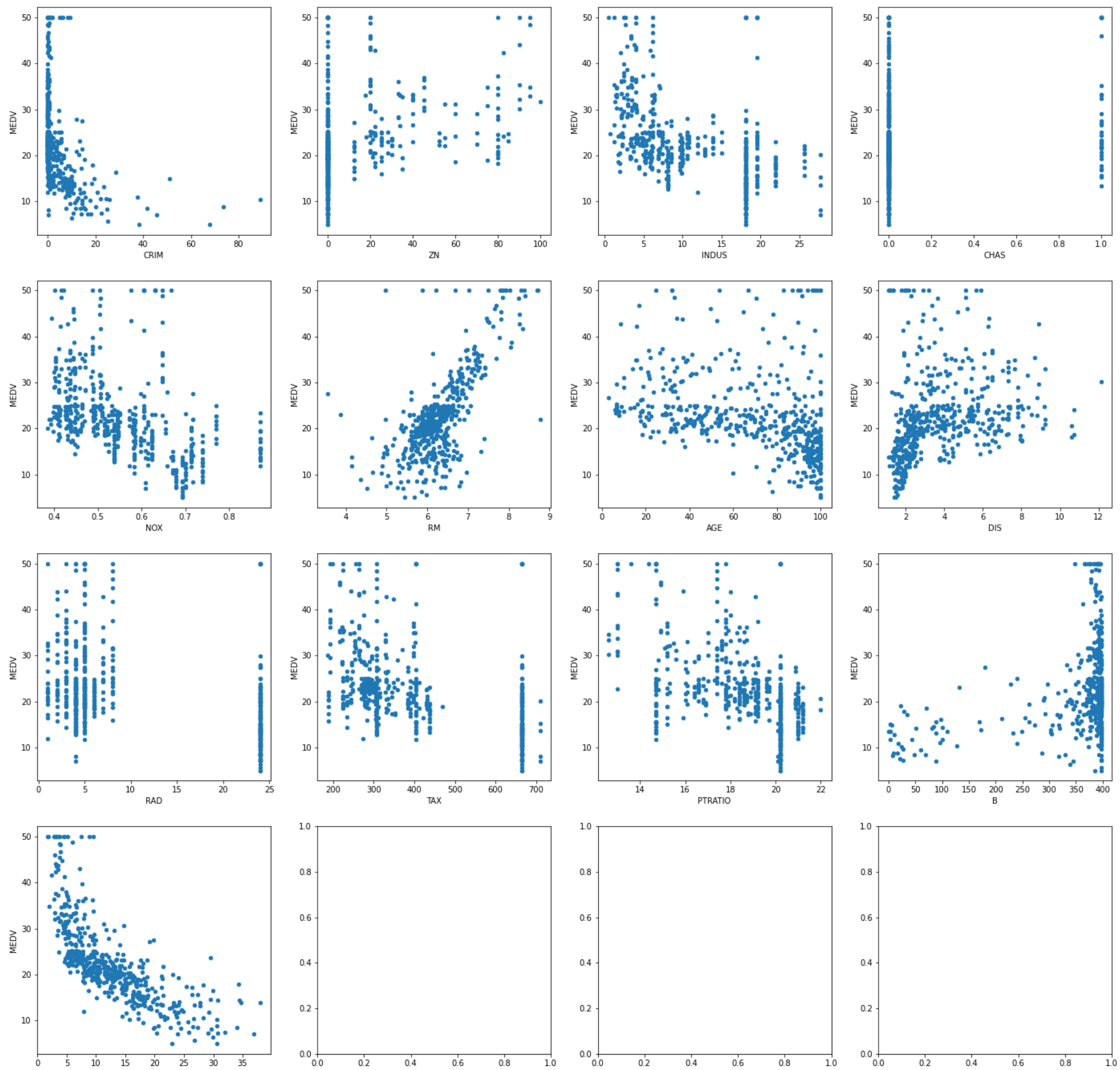
Out[9]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	
count	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506
mean	3.613524	11.363636	11.136779	0.069170	0.554695	6.284634	68.574901	3
std	8.601545	23.322453	6.860353	0.253994	0.115878	0.702617	28.148861	2
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000	2.900000	1
25%	0.082045	0.000000	5.190000	0.000000	0.449000	5.885500	45.025000	2
50%	0.256510	0.000000	9.690000	0.000000	0.538000	6.208500	77.500000	3
75%	3.677083	12.500000	18.100000	0.000000	0.624000	6.623500	94.075000	5
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000	12

In [10]:
```
bos.info()
```

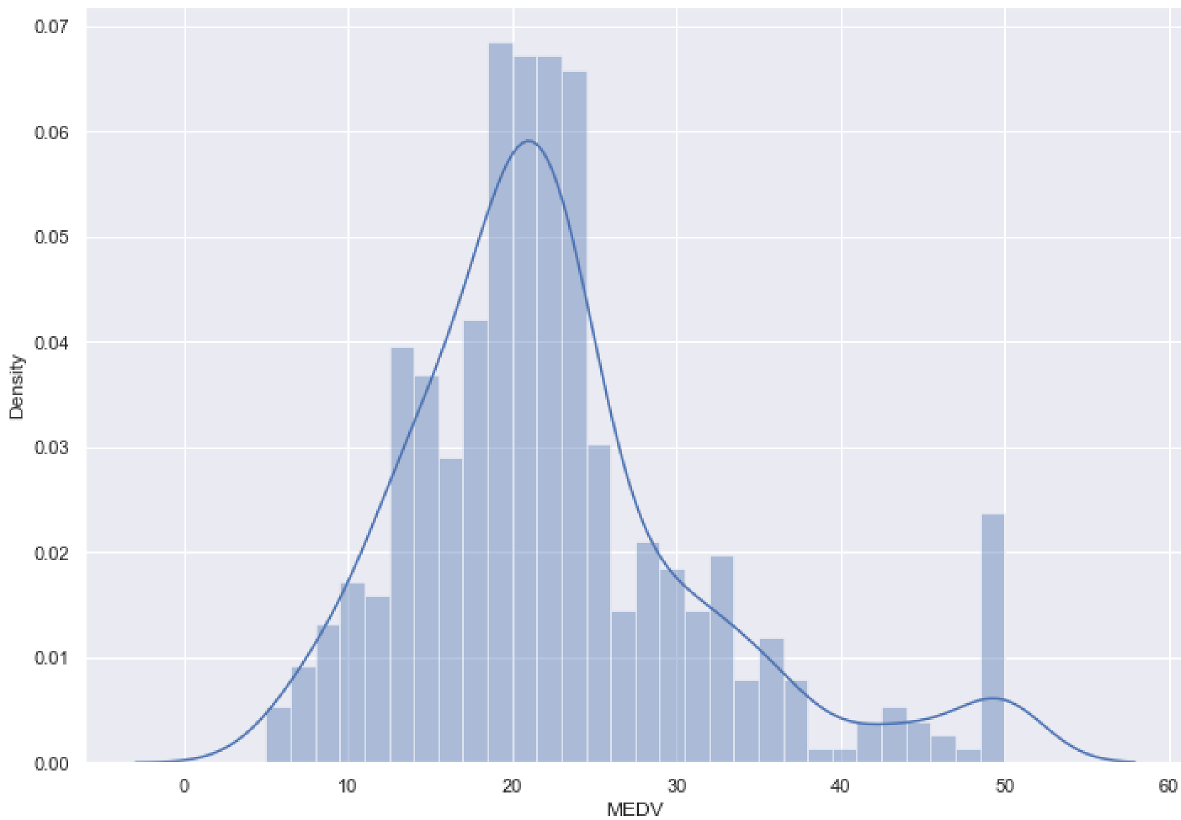
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 506 entries, 0 to 505
Data columns (total 14 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   CRIM     506 non-null    float64
 1   ZN       506 non-null    float64
 2   INDUS    506 non-null    float64
 3   CHAS     506 non-null    float64
 4   NOX      506 non-null    float64
 5   RM       506 non-null    float64
 6   AGE      506 non-null    float64
 7   DIS      506 non-null    float64
 8   RAD      506 non-null    float64
 9   TAX      506 non-null    float64
 10  PTRATIO  506 non-null    float64
 11  B        506 non-null    float64
 12  LSTAT    506 non-null    float64
 13  MEDV     506 non-null    float64
dtypes: float64(14)
memory usage: 55.5 KB
```

In [11]:
```
# visualize the relationship between the features and the response using scatt
erplots
fig, axs = plt.subplots(4, 4, figsize=(24, 24))
# unpack all the axes subplots
axe = axs.ravel()
for i in range(len(bos.drop(columns='MEDV').columns)):
    bos.plot(kind='scatter', x=bos.columns[i], y='MEDV', ax=axe[i])
    plt.xlabel(bos.columns[i])
```



In [12]:
```
sns.set(rc={'figure.figsize':(11.7,8.27)})
sns.distplot(bos['MEDV'], bins=30)
plt.show()
```

```
C:\Users\Urvi\AppData\Roaming\Python\Python37\site-packages\seaborn\distribut
ions.py:2551: FutureWarning: `distplot` is a deprecated function and will be
removed in a future version. Please adapt your code to use either `displot`
(a figure-level function with similar flexibility) or `histplot` (an axes-lev
el function for histograms).
  warnings.warn(msg, FutureWarning)
```



In [13]:
```
correlation_matrix = bos.corr().round(2)
# annot = True to print the values inside the square
sns.heatmap(data=correlation_matrix, annot=True)
```

Out[13]: <AxesSubplot:>

As seen in correlation matrix:

- LSTAT, PTRATIO, RM are highly correlated with MEDV
- TAX and RAD are highly correlated
- INDUS, NOX and AGE are high correlated with DIS
- INDUS is highly correlated with ZN, TAX, NOX

In [14]:
```
X = bos.drop(columns='MEDV')
y = bos.MEDV
```

In [15]:
```
X.shape[1]
```

Out[15]: 13

In [16]:
```
## Checking vif
vif = pd.DataFrame()
vif["VIF"] = [variance_inflation_factor(X.values, i) for i in range(X.shape[1
])]
vif["Features"] = X.columns
```

In [17]:
```
vif
```

Out[17]:

	VIF	Features
0	2.100373	CRIM
1	2.844013	ZN
2	14.485758	INDUS
3	1.152952	CHAS
4	73.894947	NOX
5	77.948283	RM
6	21.386850	AGE
7	14.699652	DIS
8	15.167725	RAD
9	61.227274	TAX
10	85.029547	PTRATIO
11	20.104943	B
12	11.102025	LSTAT

Observations in VIF:

- INDUS, NOX, RM, AGE, DIS, RAD, TAX, PTRATIO, B, LSTAT have vif > 10

In [18]:
```
## Dropping TAX, as tax and rad had high correlation
X = bos.drop(columns=['MEDV', 'TAX'])
y = bos.MEDV
## Checking vif
vif = pd.DataFrame()
vif["VIF"] = [variance_inflation_factor(X.values, i) for i in range(X.shape[1
])]
vif["Features"] = X.columns
vif
```

Out[18]:

	VIF	Features
0	2.100323	CRIM
1	2.697230	ZN
2	11.743319	INDUS
3	1.136630	CHAS
4	71.972959	NOX
5	77.946536	RM
6	21.377489	AGE
7	14.641579	DIS
8	5.599479	RAD
9	82.355181	PTRATIO
10	20.104332	B
11	11.098281	LSTAT

In [19]:
```
## Dropping NOX, as Nox and Dis, indus had high correlation
X = bos.drop(columns=['MEDV', 'TAX', 'NOX'])
y = bos.MEDV
## Checking vif
vif = pd.DataFrame()
vif["VIF"] = [variance_inflation_factor(X.values, i) for i in range(X.shape[1
])]
vif["Features"] = X.columns
vif
```

Out[19]:

	VIF	Features
0	2.098376	CRIM
1	2.696984	ZN
2	9.930116	INDUS
3	1.134868	CHAS
4	58.059674	RM
5	19.826168	AGE
6	14.485117	DIS
7	5.405429	RAD
8	82.299026	PTRATIO
9	19.872129	B
10	10.116939	LSTAT

In [20]:
```
## Dropping NOX, as Nox and Dis, indus had high correlation
X = bos.drop(columns=['MEDV', 'TAX', 'NOX', 'B', 'AGE', 'DIS'])
y = bos.MEDV
## Checking vif
vif = pd.DataFrame()
vif["VIF"] = [variance_inflation_factor(X.values, i) for i in range(X.shape[1
])]
vif["Features"] = X.columns
vif
```

Out[20]:

	VIF	Features
0	2.048566	CRIM
1	1.801368	ZN
2	8.164547	INDUS
3	1.123261	CHAS
4	43.767132	RM
5	4.867376	RAD
6	57.716508	PTRATIO
7	8.061584	LSTAT

In [21]:
```
x_train,x_test,y_train,y_test = train_test_split(X, y, test_size = 0.25, rando
m_state=355)
```

In [22]:
```
regression = LinearRegression()
regression.fit(x_train, y_train)
```

Out[22]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=Fals
e)
```

In [23]:
```
regression.score(x_train, y_train)
```

Out[23]:
```
0.6852743389124581
```

In [24]:
```
# Let's create a function to create adjusted R-Squared
def adj_r2(x,y):
    r2 = regression.score(x,y)
    n = x.shape[0]
    p = x.shape[1]
    adjusted_r2 = 1-(1-r2)*(n-1)/(n-p-1)
    return adjusted_r2
```

In [25]:
```
adj_r2(x_train,y_train)
```

Out[25]:
```
0.6784694597538086
```

In [26]:
```
lm = smf.ols(formula='MEDV ~ CRIM + ZN + INDUS + CHAS + RM + RAD + PTRATIO + L
STAT', data=bos).fit()
lm.conf_int()
```

Out[26]:

	0	1
Intercept	10.619480	27.102404
CRIM	-0.157797	-0.019711
ZN	-0.029286	0.018326
INDUS	-0.137108	0.061141
CHAS	1.523579	5.150357
RM	3.549548	5.242013
RAD	-0.012834	0.147742
PTRATIO	-1.179944	-0.668984
LSTAT	-0.647857	-0.452509

In [27]:
```
lm.summary()
```

Out[27]:

OLS Regression Results

Dep. Variable:	MEDV	**R-squared:**	0.692
Model:	OLS	**Adj. R-squared:**	0.687
Method:	Least Squares	**F-statistic:**	139.5
Date:	Fri, 15 Jan 2021	**Prob (F-statistic):**	7.94e-122
Time:	20:49:17	**Log-Likelihood:**	-1542.4
No. Observations:	506	**AIC:**	3103.
Df Residuals:	497	**BIC:**	3141.
Df Model:	8		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	18.8609	4.195	4.496	0.000	10.619	27.102
CRIM	-0.0888	0.035	-2.526	0.012	-0.158	-0.020
ZN	-0.0055	0.012	-0.452	0.651	-0.029	0.018
INDUS	-0.0380	0.050	-0.753	0.452	-0.137	0.061
CHAS	3.3370	0.923	3.615	0.000	1.524	5.150
RM	4.3958	0.431	10.206	0.000	3.550	5.242
RAD	0.0675	0.041	1.651	0.099	-0.013	0.148
PTRATIO	-0.9245	0.130	-7.110	0.000	-1.180	-0.669
LSTAT	-0.5502	0.050	-11.067	0.000	-0.648	-0.453

Omnibus:	184.679	**Durbin-Watson:**	0.978
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	851.037
Skew:	1.567	**Prob(JB):**	1.58e-185
Kurtosis:	8.527	**Cond. No.**	579.

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

As p values for ZN and INDUS > 0.05, we fail to reject null hypothesis. Hence, there is no correlation between MEDV and ZN, INDUS. So, we drop them

In [28]:
```
lm = smf.ols(formula='MEDV ~ CRIM + CHAS + RM + RAD + PTRATIO + LSTAT', data=b
os).fit()
lm.summary()
```

Out[28]:

OLS Regression Results

Dep. Variable:	MEDV	**R-squared:**	0.691
Model:	OLS	**Adj. R-squared:**	0.688
Method:	Least Squares	**F-statistic:**	186.4
Date:	Fri, 15 Jan 2021	**Prob (F-statistic):**	5.75e-124
Time:	20:49:17	**Log-Likelihood:**	-1542.7
No. Observations:	506	**AIC:**	3099.
Df Residuals:	499	**BIC:**	3129.
Df Model:	6		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	18.2899	4.086	4.476	0.000	10.262	26.318
CRIM	-0.0885	0.035	-2.527	0.012	-0.157	-0.020
CHAS	3.2827	0.912	3.601	0.000	1.492	5.074
RM	4.4174	0.428	10.316	0.000	3.576	5.259
RAD	0.0567	0.038	1.497	0.135	-0.018	0.131
PTRATIO	-0.9159	0.126	-7.274	0.000	-1.163	-0.668
LSTAT	-0.5583	0.047	-11.950	0.000	-0.650	-0.467

Omnibus:	182.840	**Durbin-Watson:**	0.979
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	833.465
Skew:	1.553	**Prob(JB):**	1.04e-181
Kurtosis:	8.467	**Cond. No.**	478.

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

As p values for RAD > 0.05, we fail to reject null hypothesis. Hence, there is no correlation between MEDV and RAD. So, we drop them

In [29]:
```
lm = smf.ols(formula='MEDV ~ CRIM + CHAS + RM + PTRATIO + LSTAT', data=bos).fi
t()
lm.summary()
```

Out[29]:

OLS Regression Results

Dep. Variable:	MEDV	**R-squared:**	0.690
Model:	OLS	**Adj. R-squared:**	0.687
Method:	Least Squares	**F-statistic:**	222.7
Date:	Fri, 15 Jan 2021	**Prob (F-statistic):**	1.11e-124
Time:	20:49:17	**Log-Likelihood:**	-1543.9
No. Observations:	506	**AIC:**	3100.
Df Residuals:	500	**BIC:**	3125.
Df Model:	5		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	16.5736	3.927	4.221	0.000	8.859	24.288
CRIM	-0.0625	0.030	-2.052	0.041	-0.122	-0.003
CHAS	3.3879	0.910	3.723	0.000	1.600	5.176
RM	4.5262	0.423	10.713	0.000	3.696	5.356
PTRATIO	-0.8489	0.118	-7.204	0.000	-1.080	-0.617
LSTAT	-0.5397	0.045	-11.970	0.000	-0.628	-0.451

Omnibus:	198.984	**Durbin-Watson:**	0.968
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1006.250
Skew:	1.670	**Prob(JB):**	3.13e-219
Kurtosis:	9.048	**Cond. No.**	417.

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [30]:
```
bos.columns
```

Out[30]:
```
Index(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD', 'TA
X',
       'PTRATIO', 'B', 'LSTAT', 'MEDV'],
      dtype='object')
```

In [31]:
```
X = bos.drop(columns=['ZN', 'INDUS', 'NOX', 'AGE', 'DIS', 'RAD', 'TAX', 'B'])
x_train,x_test,y_train,y_test = train_test_split(X, y, test_size = 0.25, rando
m_state=355)
regression = LinearRegression()
regression.fit(x_train, y_train)
regression.score(x_test,y_test)
```

Out[31]: 1.0

In [32]:
```
adj_r2(x_test,y_test)
```

Out[32]: 1.0

In [33]:
```
# Lasso Regularization
# LassoCV will return best alpha and coefficients after performing 10 cross va
lidations
lasscv = LassoCV(alphas = None,cv =10, max_iter = 100000, normalize = True)
lasscv.fit(x_train, y_train)
```

Out[33]:
```
LassoCV(alphas=None, copy_X=True, cv=10, eps=0.001, fit_intercept=True,
        max_iter=100000, n_alphas=100, n_jobs=None, normalize=True,
        positive=False, precompute='auto', random_state=None,
        selection='cyclic', tol=0.0001, verbose=False)
```

In [34]:
```
# best alpha parameter
alpha = lasscv.alpha_
alpha
```

Out[34]: 0.00046719468953559777

In [35]:
```
#now that we have best parameter, let's use Lasso regression and see how well
 our data has fitted before

lasso_reg = Lasso(alpha)
lasso_reg.fit(x_train, y_train)
```

Out[35]:
```
Lasso(alpha=0.00046719468953559777, copy_X=True, fit_intercept=True,
      max_iter=1000, normalize=False, positive=False, precompute=False,
      random_state=None, selection='cyclic', tol=0.0001, warm_start=False)
```

In [36]:
```
lasso_reg.score(x_test, y_test)
```

Out[36]: 0.9999999999681303

In [37]:
```
# Using Ridge regression model
# RidgeCV will return best alpha and coefficients after performing 10 cross va
lidations.
# We will pass an array of random numbers for ridgeCV to select best alpha fro
m them

alphas = np.random.uniform(low=0, high=10, size=(50,))
ridgecv = RidgeCV(alphas = alphas,cv=10,normalize = True)
ridgecv.fit(x_train, y_train)
```

Out[37]:
```
RidgeCV(alphas=array([3.28930915, 7.89545669, 1.6628005 , 6.70285091, 2.74752
509,
       7.14862378, 4.11504209, 8.03652793, 6.05656481, 0.33067785,
       3.69672012, 7.11045599, 2.15930961, 7.92899791, 4.52094033,
       8.66256149, 7.82366878, 3.48542093, 3.9133991 , 1.3756095 ,
       4.62807315, 2.88971323, 0.44889159, 8.11791991, 5.09407137,
       7.30088967, 5.44378713, 4.94060507, 6.42312384, 0.8735612 ,
       7.10870453, 7.49889476, 6.7303034 , 1.54226575, 7.58070917,
       3.83952096, 6.47679764, 2.56581659, 3.02340132, 7.05430819,
       5.50345811, 8.08686833, 9.2267722 , 5.65233148, 4.02877869,
       8.39449767, 3.76151812, 6.30254226, 4.0210066 , 7.70982734]),
        cv=10, fit_intercept=True, gcv_mode=None, normalize=True, scoring=Non
e,
        store_cv_values=False)
```

In [38]:
```
ridgecv.alpha_
```

Out[38]:
```
0.33067784763377017
```

In [39]:
```
ridge_model = Ridge(alpha=ridgecv.alpha_)
ridge_model.fit(x_train, y_train)
```

Out[39]:
```
Ridge(alpha=0.33067784763377017, copy_X=True, fit_intercept=True, max_iter=No
ne,
      normalize=False, random_state=None, solver='auto', tol=0.001)
```

In [40]:
```
ridge_model.score(x_test, y_test)
```

Out[40]:
```
0.9999999996706648
```

As Lasso, Ridge and Linear Regression Test score is almost same, model is not overfitted.

In [41]:
```
# Elastic net

elasticCV = ElasticNetCV(alphas = None, cv =10)
elasticCV.fit(x_train, y_train)
```

Out[41]:
```
ElasticNetCV(alphas=None, copy_X=True, cv=10, eps=0.001, fit_intercept=True,
             l1_ratio=0.5, max_iter=1000, n_alphas=100, n_jobs=None,
             normalize=False, positive=False, precompute='auto',
             random_state=None, selection='cyclic', tol=0.0001, verbose=0)
```

In [42]:
```
elasticCV.alpha_
```

Out[42]:
```
0.1654493254711398
```

In [43]:
```
elasticCV.l1_ratio
```

Out[43]:
```
0.5
```

In [44]:
```
elasticnet_reg = ElasticNet(alpha=elasticCV.alpha_, l1_ratio=0.5)
elasticnet_reg.fit(x_train, y_train)
```

Out[44]:
```
ElasticNet(alpha=0.1654493254711398, copy_X=True, fit_intercept=True,
           l1_ratio=0.5, max_iter=1000, normalize=False, positive=False,
           precompute=False, random_state=None, selection='cyclic', tol=0.000
1,
           warm_start=False)
```

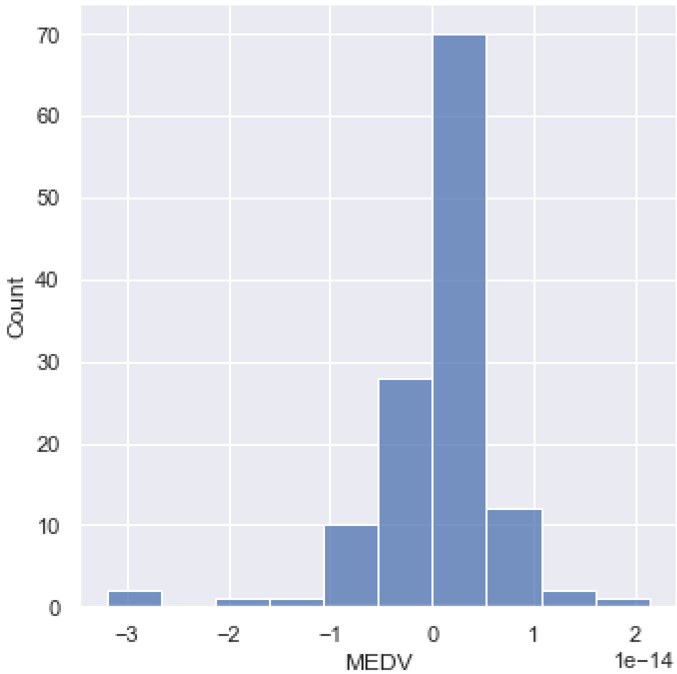
In [45]:
```
elasticnet_reg.score(x_test, y_test)
```

Out[45]:
```
0.9999959500003314
```

In [46]:
```
# model evaluation for training set
y_train_predict = regression.predict(x_train)
rmse = (np.sqrt(mean_squared_error(y_train, y_train_predict)))
r2 = r2_score(y_train, y_train_predict)

print("The model performance for training set")
print("--------------------------------------")
print('RMSE is {}'.format(rmse))
print('R2 score is {}'.format(r2))
print("\n")

# model evaluation for testing set
y_test_predict = regression.predict(x_test)
rmse = (np.sqrt(mean_squared_error(y_test, y_test_predict)))
r2 = r2_score(y_test, y_test_predict)

print("The model performance for testing set")
print("--------------------------------------")
print('RMSE is {}'.format(rmse))
print('R2 score is {}'.format(r2))
```

```
The model performance for training set
--------------------------------------
RMSE is 5.620667389044694e-15
R2 score is 1.0


The model performance for testing set
--------------------------------------
RMSE is 6.342862616064737 6e-15
R2 score is 1.0
```

In [62]:
```
predicted = regression.predict(x_test)
residuals = y_test-predicted
sns.set(rc={'figure.figsize':(11,8)})
sns.displot(residuals, bins=10)
plt.show()
```



In [64]:
```
# mean of residuals is almost 0
residuals.mean()
```

Out[64]: -6.224242468764657e-16

In [65]:
```
## Hence all the assumptions are satisfied
```

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In [ ]: