Submitted by Navneet Das 3433 Comp A

***'
Assignment 1 Deep Learning
Implement Boston housing price prediction problem regression methods using Deep Neural network.
Use the Boston House price prediction dataset.
Use Polynomial Regression, Lasso Regression, Partial least regression, Ordinal Regression, and linear & logistic regression. Compare the results for performance analysis
***

In [2]:
```
import numpy as np
import pandas as pd
```

In [3]:
```
data_url = "DeepLearningData/housing.xls"
raw_df = pd.read_csv(data_url, sep="\s+", skiprows=22, header=None)
data = np.hstack([raw_df.values[::2, :], raw_df.values[1::2, :2]])
target = raw_df.values[1::2, 2]
```

In [4]:
```
raw_df
```

Out[4]:

	0	1	2	3	4	5	6	7	8	9	10	11	12	13
0	1.23247	0.0	8.14	0	0.538	6.142	91.7	3.9769	4	307.0	21.0	396.90	18.72	15.2
1	0.98843	0.0	8.14	0	0.538	5.813	100.0	4.0952	4	307.0	21.0	394.54	19.88	14.5
2	0.75026	0.0	8.14	0	0.538	5.924	94.1	4.3996	4	307.0	21.0	394.33	16.30	15.6
3	0.84054	0.0	8.14	0	0.538	5.599	85.7	4.4546	4	307.0	21.0	303.42	16.51	13.9
4	0.67191	0.0	8.14	0	0.538	5.813	90.3	4.6820	4	307.0	21.0	376.88	14.81	16.6
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
479	0.06263	0.0	11.93	0	0.573	6.593	69.1	2.4786	1	273.0	21.0	391.99	9.67	22.4
480	0.04527	0.0	11.93	0	0.573	6.120	76.7	2.2875	1	273.0	21.0	396.90	9.08	20.6
481	0.06076	0.0	11.93	0	0.573	6.976	91.0	2.1675	1	273.0	21.0	396.90	5.64	23.9
482	0.10959	0.0	11.93	0	0.573	6.794	89.3	2.3889	1	273.0	21.0	393.45	6.48	22.0
483	0.04741	0.0	11.93	0	0.573	6.030	80.8	2.5050	1	273.0	21.0	396.90	7.88	11.9

484 rows × 14 columns

In [5]:
```
# from sklearn.datasets import load_boston
# boston = load_boston()
```

In [6]:
```
data = pd.DataFrame(raw_df)
```

In [7]:
```
data.head()
```

Out[7]:

	0	1	2	3	4	5	6	7	8	9	10	11	12	13
0	1.23247	0.0	8.14	0	0.538	6.142	91.7	3.9769	4	307.0	21.0	396.90	18.72	15.2
1	0.98843	0.0	8.14	0	0.538	5.813	100.0	4.0952	4	307.0	21.0	394.54	19.88	14.5
2	0.75026	0.0	8.14	0	0.538	5.924	94.1	4.3996	4	307.0	21.0	394.33	16.30	15.6
3	0.84054	0.0	8.14	0	0.538	5.599	85.7	4.4546	4	307.0	21.0	303.42	16.51	13.9
4	0.67191	0.0	8.14	0	0.538	5.813	90.3	4.6820	4	307.0	21.0	376.88	14.81	16.6

In [8]:
```
data.columns = ['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD', 'TAX', 'PTRATIO', 'B', 'LSTAT',"PRIC
```

In [ ]:
```

```

In [9]:
```
data.head()
```

Out[9]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	PRICE
0	1.23247	0.0	8.14	0	0.538	6.142	91.7	3.9769	4	307.0	21.0	396.90	18.72	15.2
1	0.98843	0.0	8.14	0	0.538	5.813	100.0	4.0952	4	307.0	21.0	394.54	19.88	14.5
2	0.75026	0.0	8.14	0	0.538	5.924	94.1	4.3996	4	307.0	21.0	394.33	16.30	15.6
3	0.84054	0.0	8.14	0	0.538	5.599	85.7	4.4546	4	307.0	21.0	303.42	16.51	13.9
4	0.67191	0.0	8.14	0	0.538	5.813	90.3	4.6820	4	307.0	21.0	376.88	14.81	16.6

In [10]:
```
data.to_csv("DeepLearningData/boston.csv",index=False)
```

In [11]:
```
print(data.shape)
```

```
(484, 14)
```

In [12]:
```
data.isnull().sum()
```

Out[12]:
```
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
PRICE      0
dtype: int64
```

No null values in the dataset, no missing value treatement needed

In [13]:
```
data.describe()
```

Out[13]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	
count	484.000000	484.000000	484.000000	484.000000	484.000000	484.000000	484.000000	484.000000	484.000000	484.000000	484.000000	484.
mean	3.759989	11.662190	11.330310	0.072314	0.556437	6.290605	68.518595	3.735627	9.807851	413.599174	18.463017	355.
std	8.766728	23.764895	6.936898	0.259275	0.118018	0.710895	28.447452	2.124833	8.813355	170.252171	2.145556	92.
min	0.009060	0.000000	0.460000	0.000000	0.385000	3.561000	2.900000	1.129600	1.000000	187.000000	12.600000	0.
25%	0.082155	0.000000	5.130000	0.000000	0.448000	5.884750	43.625000	2.064700	4.000000	279.000000	17.400000	374.
50%	0.262660	0.000000	9.900000	0.000000	0.538000	6.211500	77.700000	3.057250	5.000000	345.000000	19.100000	391.
75%	3.896877	20.000000	18.100000	0.000000	0.631000	6.630000	94.100000	5.116700	24.000000	666.000000	20.200000	396.
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000	12.126500	24.000000	711.000000	22.000000	396.

This is sometimes very useful, for example if you look at the CRIM the max is 88.97 and 75% of the value is below 3.677083 and mean is 3.613524 so it means the max values is actually an outlier or there are outliers present in the column

In [14]:
```
data.info()
```

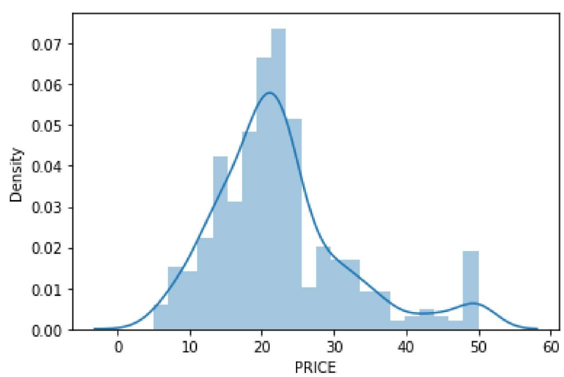
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 484 entries, 0 to 483
Data columns (total 14 columns):
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0   CRIM     484 non-null    float64
 1   ZN       484 non-null    float64
 2   INDUS    484 non-null    float64
 3   CHAS     484 non-null    int64
 4   NOX      484 non-null    float64
 5   RM       484 non-null    float64
 6   AGE      484 non-null    float64
 7   DIS      484 non-null    float64
 8   RAD      484 non-null    int64
 9   TAX      484 non-null    float64
 10  PTRATIO  484 non-null    float64
 11  B        484 non-null    float64
 12  LSTAT    484 non-null    float64
 13  PRICE    484 non-null    float64
dtypes: float64(12), int64(2)
memory usage: 53.1 KB
```

Visualisation

In [15]:
```
import seaborn as sns
sns.distplot(data.PRICE)
```

```
C:\Users\navne\anaconda3\lib\site-packages\seaborn\distributions.py:2619: 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 fun
ction with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[15]:
```
<AxesSubplot:xlabel='PRICE', ylabel='Density'>
```

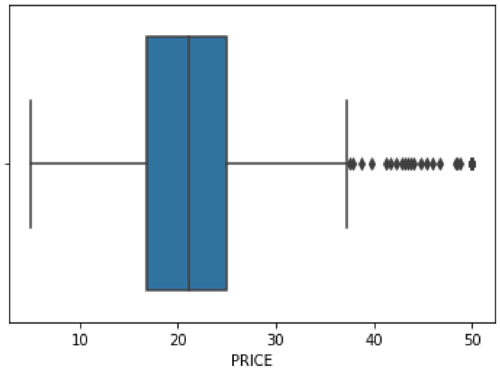


The distribution seems normal, has not be the data normal we would have perform log transformation or took to square root of the data to make the data normal. Normal distribution is need for the machine learning for better predictiblity of the model

In [16]:
```
sns.boxplot(data.PRICE)
```

```
C:\Users\navne\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable as
a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments
without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[16]:
```
<AxesSubplot:xlabel='PRICE'>
```



Checking the correlation of the independent feature with the dependent feature

Correlation is a statistical technique that can show whether and how strongly pairs of variables are related.An intelligent correlation analysis can lead to a greater understanding of your data

In [17]:
```
correlation = data.corr()
correlation.loc['PRICE']
```

Out[17]:
```
CRIM      -0.393057
ZN         0.366270
INDUS     -0.488006
CHAS       0.176896
NOX       -0.427658
RM         0.693071
AGE       -0.374692
DIS        0.252464
RAD       -0.388123
TAX       -0.475074
PTRATIO   -0.525636
B          0.336935
LSTAT     -0.740927
PRICE      1.000000
Name: PRICE, dtype: float64
```

In [18]:

```python
import matplotlib.pyplot as plt
fig,axes = plt.subplots(figsize=(15,12))
sns.heatmap(correlation,square = True,annot = True)
```

Out[18]: <AxesSubplot:>

By looking at the correlation plot LSAT is negatively correlated with -0.75 and RM is positively correlated to the price and PTRATIO is correlated negatively with -0.51

In [19]:

```python
plt.figure(figsize = (20,5))
features = ['LSTAT','RM','PTRATIO']
for i, col in enumerate(features):
    plt.subplot(1, len(features) , i+1)
    x = data[col]
    y = data.PRICE
    plt.scatter(x, y, marker='o')
    plt.title("Variation in House prices")
    plt.xlabel(col)
    plt.ylabel('"House prices in $1000"')
```

Splitting the dependent feature and independent feature

In [20]:
```
X = data.iloc[:,:-1]
y= data.PRICE
```

In [21]:
```
!pip install mord
```

```
Collecting mord
  Downloading mord-0.6.tar.gz (4.7 kB)
  Preparing metadata (setup.py): started
  Preparing metadata (setup.py): finished with status 'done'
Building wheels for collected packages: mord
  Building wheel for mord (setup.py): started
  Building wheel for mord (setup.py): finished with status 'done'
  Created wheel for mord: filename=mord-0.6-py3-none-any.whl size=5985 sha256=70da32e2bcb5889f91581a6e6d79f984c42ff2
f7f928e6aaa53aa27651b8606b
  Stored in directory: c:\users\navne\appdata\local\pip\cache\wheels\1e\fa\70\c1078bd598530116799d668f190e1c52f713cd
9329dcb2df37
Successfully built mord
Installing collected packages: mord
Successfully installed mord-0.6

  WARNING: Retrying (Retry(total=4, connect=None, read=None, redirect=None, status=None)) after connection broken by
'ConnectTimeoutError(<pip._vendor.urllib3.connection.HTTPSConnection object at 0x000002077D051970>, 'Connection to f
iles.pythonhosted.org timed out. (connect timeout=15)')': /packages/67/9d/c791c841501d9ff4ecb76b57f208dec6cf9f925109
c59c995ddec80f9b32/mord-0.6.tar.gz

[notice] A new release of pip is available: 23.0.1 -> 23.1.2
[notice] To update, run: python.exe -m pip install --upgrade pip
```

In [22]:
```
!pip install tabulate
```

```
Requirement already satisfied: tabulate in c:\users\navne\anaconda3\lib\site-packages (0.8.9)


[notice] A new release of pip is available: 23.0.1 -> 23.1.2
[notice] To update, run: python.exe -m pip install --upgrade pip
```

In [23]:
```python
import numpy as np
# from sklearn.datasets import load_boston
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression, Lasso
from sklearn.preprocessing import PolynomialFeatures, StandardScaler
from sklearn.pipeline import make_pipeline
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.cross_decomposition import PLSRegression
from mord import OrdinalRidge
from tabulate import tabulate



X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Polynomial Regression
poly_reg = make_pipeline(PolynomialFeatures(degree=2), StandardScaler(), LinearRegression())
poly_reg.fit(X_train, y_train)
y_pred_poly = poly_reg.predict(X_test)
poly_mse = mean_squared_error(y_test, y_pred_poly)
poly_r2 = r2_score(y_test, y_pred_poly)

# Lasso Regression
lasso_reg = make_pipeline(StandardScaler(), Lasso(alpha=0.1))
lasso_reg.fit(X_train, y_train)
y_pred_lasso = lasso_reg.predict(X_test)
lasso_mse = mean_squared_error(y_test, y_pred_lasso)
lasso_r2 = r2_score(y_test, y_pred_lasso)

# Partial Least Squares Regression
pls_reg = make_pipeline(StandardScaler(), PLSRegression(n_components=5))
pls_reg.fit(X_train, y_train)
y_pred_pls = pls_reg.predict(X_test)
pls_mse = mean_squared_error(y_test, y_pred_pls)
pls_r2 = r2_score(y_test, y_pred_pls)

# Ordinal Regression
ordinal_reg = OrdinalRidge(alpha=0.1)
ordinal_reg.fit(X_train, y_train)
y_pred_ordinal = ordinal_reg.predict(X_test)
ordinal_mse = mean_squared_error(y_test, y_pred_ordinal)
ordinal_r2 = r2_score(y_test, y_pred_ordinal)

# Linear Regression
linear_reg = LinearRegression()
linear_reg.fit(X_train, y_train)
y_pred_linear = linear_reg.predict(X_test)
linear_mse = mean_squared_error(y_test, y_pred_linear)
linear_r2 = r2_score(y_test, y_pred_linear)


table = [
    ["Polynomial Regression", poly_mse, poly_r2],
    ["Lasso Regression", lasso_mse, lasso_r2],
    ["Partial Least Squares Regression", pls_mse, pls_r2],
    ["Ordinal Regression", ordinal_mse, ordinal_r2],
    ["Linear Regression", linear_mse, linear_r2]
]


headers = ["Model", "Mean Squared Error", "R2 Score"]
print(tabulate(table, headers, tablefmt="grid"))
```

```
+----------------------------------+----------------------+------------+
| Model                            |   Mean Squared Error |   R2 Score |
+==================================+======================+============+
| Polynomial Regression            |              15.367  |   0.825619 |
+----------------------------------+----------------------+------------+
| Lasso Regression                 |              19.8478 |   0.774772 |
+----------------------------------+----------------------+------------+
| Partial Least Squares Regression |              20.5179 |   0.767167 |
+----------------------------------+----------------------+------------+
| Ordinal Regression               |              20.4365 |   0.768091 |
+----------------------------------+----------------------+------------+
| Linear Regression                |              20.1437 |   0.771415 |
+----------------------------------+----------------------+------------+
```

Neural Networks

In [24]:
```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

In [25]:
```
import keras
from keras.layers import Dense, Activation,Dropout
from keras.models import Sequential

model = Sequential()

model.add(Dense(128,activation  = 'relu',input_dim =13))
model.add(Dense(64,activation  = 'relu'))
model.add(Dense(32,activation  = 'relu'))
model.add(Dense(16,activation  = 'relu'))
# model.add(Dense(8,activation  = 'relu'))
model.add(Dense(1))
model.compile(optimizer = 'adam',loss = 'mean_squared_error')
```

In [26]:
```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 dense (Dense)               (None, 128)               1792      
                                                                 
 dense_1 (Dense)             (None, 64)                8256      
                                                                 
 dense_2 (Dense)             (None, 32)                2080      
                                                                 
 dense_3 (Dense)             (None, 16)                528       
                                                                 
 dense_4 (Dense)             (None, 1)                 17        
                                                                 
=================================================================
Total params: 12,673
Trainable params: 12,673
Non-trainable params: 0
_________________________________________________________________
```

In [27]:
```
!pip install graphviz
```

```
Collecting graphviz
  Downloading graphviz-0.20.1-py3-none-any.whl (47 kB)
     ---------------------------------------- 47.0/47.0 kB 2.5 MB/s eta 0:00:00
Installing collected packages: graphviz
Successfully installed graphviz-0.20.1


[notice] A new release of pip is available: 23.0.1 -> 23.1.2
[notice] To update, run: python.exe -m pip install --upgrade pip
```

In [28]:
```
from keras.utils.vis_utils import plot_model
plot_model(model, to_file='model_plot.png', show_shapes=True, show_layer_names=True)
```

You must install pydot (`pip install pydot`) and install graphviz (see instructions at https://graphviz.gitlab.io/download/) (https://graphviz.gitlab.io/download/)) for plot_model to work.

In [29]:
```
model.fit(X_train, y_train, epochs = 100)
```

```
Epoch 29/100
13/13 [==============================] - 0s 2ms/step - loss: 11.2175
Epoch 30/100
13/13 [==============================] - 0s 2ms/step - loss: 10.8211
Epoch 31/100
13/13 [==============================] - 0s 2ms/step - loss: 10.2924
Epoch 32/100
13/13 [==============================] - 0s 2ms/step - loss: 10.4162
Epoch 33/100
13/13 [==============================] - 0s 2ms/step - loss: 10.0125
Epoch 34/100
13/13 [==============================] - 0s 2ms/step - loss: 10.1418
Epoch 35/100
13/13 [==============================] - 0s 2ms/step - loss: 9.7660
Epoch 36/100
13/13 [==============================] - 0s 1ms/step - loss: 9.5556
Epoch 37/100
13/13 [==============================] - 0s 2ms/step - loss: 9.7917
Epoch 38/100
13/13 [==============================] - 0s 2ms/step - loss: 9.3827
```

Evaluation of the model

In [30]:
```
y_pred_nn = model.predict(X_test)
nn_mse = mean_squared_error(y_test, y_pred_nn)
```

```
4/4 [==============================] - 0s 2ms/step
```

In [31]:
```
from sklearn.metrics import r2_score
nn_r2 = r2_score(y_test, y_pred_nn)
print(nn_r2)
```

```
0.910074742473124
```

In [32]:
```
table = [
    ["Polynomial Regression", poly_mse, poly_r2],
    ["Lasso Regression", lasso_mse, lasso_r2],
    ["Partial Least Squares Regression", pls_mse, pls_r2],
    ["Ordinal Regression", ordinal_mse, ordinal_r2],
    ["Linear Regression", linear_mse, linear_r2],
    ["Neural Network Regression Model",nn_mse,nn_r2 ]
]


headers = ["Model", "Mean Squared Error", "R2 Score"]
print(tabulate(table, headers, tablefmt="markdown"))
```

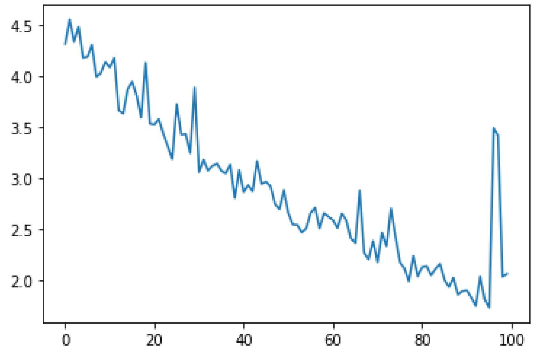
```
Model                               Mean Squared Error    R2 Score
--------------------------------  --------------------  ----------
Polynomial Regression                         15.367      0.825619
Lasso Regression                              19.8478     0.774772
Partial Least Squares Regression              20.5179     0.767167
Ordinal Regression                            20.4365     0.768091
Linear Regression                             20.1437     0.771415
Neural Network Regression Model                7.92449    0.910075
```

In [33]:
```python
lossv = []
for epoch in range (100):
    history = model.fit(X_train, y_train, epochs = 1)
    lossv += history.history['loss']

plt.plot(lossv)
```

```
13/13 [==============================] - 0s 2ms/step - loss: 2.0319
13/13 [==============================] - 0s 1ms/step - loss: 2.0599
```

Out[33]: [<matplotlib.lines.Line2D at 0x28cf1d2e5e0>]



In [ ]: