Implement SGD on Linear Regression using Boston Home Price Dataset

In [2]:
```
import warnings
warnings.filterwarnings("ignore")
```

In [3]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

from sklearn.datasets import load_boston
from sklearn.cross_validation import train_test_split
from sklearn.metrics import mean_squared_error

from sklearn.linear_model import SGDRegressor
from sklearn.preprocessing import StandardScaler
```

```
C:\Users\GauravP\Anaconda3\lib\site-packages\sklearn\cross_validation.py:41: DeprecationWarning: This module was deprec
ated in version 0.18 in favor of the model_selection module into which all the refactored classes and functions are mov
ed. Also note that the interface of the new CV iterators are different from that of this module. This module will be re
moved in 0.20.
  "This module will be removed in 0.20.", DeprecationWarning)
```

In [4]:
```
boston = load_boston()
```

In [5]:
```
print(boston.DESCR)
```

```
Boston House Prices dataset
===========================

Notes
------
Data Set Characteristics:

    :Number of Instances: 506

    :Number of Attributes: 13 numeric/categorical predictive

    :Median Value (attribute 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.
http://archive.ics.uci.edu/ml/datasets/Housing (http://archive.ics.uci.edu/ml/datasets/Housing)


This dataset was taken from the StatLib library which is maintained at Carnegie 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 that address regression
problems.

**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 Co
nference of Machine Learning, 236-243, University of Massachusetts, Amherst. Morgan Kaufmann.
   - many more! (see http://archive.ics.uci.edu/ml/datasets/Housing) (http://archive.ics.uci.edu/ml/datasets/Housing))
```

In [6]:
```
boston.data.shape
```

Out[6]:
```
(506, 13)
```

In [7]:
```
columnNames = boston.feature_names
columnNames
```

Out[7]:
```
array(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD',
       'TAX', 'PTRATIO', 'B', 'LSTAT'], dtype='<U7')
```

In [8]:
```
Data = pd.DataFrame(boston.data, columns = columnNames)
```

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

Out[9]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT
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	4.98
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	9.14
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	4.03
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	2.94
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	5.33

In [10]:
```
Data_Labels = boston.target
Data_Labels.shape
```

Out[10]:
```
(506,)
```

In [11]:
```
Data["PRICE"] = Data_Labels
```

In [12]:
```
Data.head()
```

Out[12]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	PRICE
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	4.98	24.0
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	9.14	21.6
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	4.03	34.7
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	2.94	33.4
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	5.33	36.2

In [13]:
```
Data.shape
```

Out[13]:
```
(506, 14)
```

In [14]:
```
# weight = np.random.rand(13, 1)  # defining initial random weight
```

In [15]:
```
# weight
```

In [16]:
```
# print(type(weight))
```

In [17]:
```
# b = np.random.random()   # generating initial random y-intercept
# b
```

In [18]:
```
# np.dot(weight.T, Data.iloc[0])
```

In [19]:
```
# for i in range(len(weight)):
#     weight[i][0] = weight[i][0] - Data.iloc[0].values[i]
```

In [20]:
```
# weight
```

In [21]:
```
# print(Data.iloc[0].values[0])
```

In [22]:
```
# weight[11][0]
```

In [23]:
```
X_train, X_test, Y_train, Y_test = train_test_split(Data, Data["PRICE"], test_size = 0.2)

X_train.shape, X_test.shape, Y_train.shape, Y_test.shape
```

Out[23]:
```
((404, 14), (102, 14), (404,), (102,))
```

In [24]:
```
m = X_train.shape[0]
```

Performing Stochastic Gradient Descent by taking 10 random samples

In [25]:
```
weight = np.random.randn(13)*np.sqrt(2/m)   # defining initial random weight from normal distribution
b = np.random.randn(1)*np.sqrt(2/m)   # generating initial random y-intercept from normal distribution

learningRate = 0.2

for i in range(2500):    # running 2500 iterations
    Data_batch_10 = X_train.sample(n = 10)   # taking 10 stochastic samples
    X_temp = Data_batch_10.drop("PRICE", axis = 1, inplace = False)
    X_std = StandardScaler().fit_transform(X_temp)
    X = pd.DataFrame(X_std, columns = columnNames)
    Y = Data_batch_10["PRICE"]
    PartialGradient = np.empty(13)
    sum2 = 0

    for j in range(13):     # as there are 13 dimensions in our dataset and dimensions of weight should also be same as d
        sum1 = 0
        for k in range(10):
            sum1 += -2 * X.iloc[k][j] * (Y.iloc[k] - np.dot(weight, X.iloc[k]) - b)  # this is a derivative of linear reg
        PartialGradient[j] = sum1
    PartialGradient *= learningRate
#     print("Partial Gradient = "+str(PartialGradient))
#     print("Iteration number = "+str(i))

    for m in range(10):
        sum2 += -2 * (Y.iloc[m]- np.dot(weight, X.iloc[m]) - b)     # this is the derivative of linear regression w.r.t '
    b = b - learningRate * sum2       #updating y-intercept 'b'


    for l in range(13):
        weight[l] -= PartialGradient[l]  # updating weights

    learningRate = 0.01 / pow(i+1, 0.25)     #learning rate at every iteration

    weight = weight + 0.0001*np.dot(weight, weight)   #adding l2 regularization
    b = b + 0.0001*np.dot(weight, weight) #adding L2 regularization

print("Weight = "+str(weight))
print("b = "+str(b))
```

```
Weight = [-0.32149077  0.9982537   0.29047732  1.27605095 -1.06511298  3.04382499
```

```
  1.05440704 -1.84683024  2.35400459 -1.59350102 -1.53593969  0.60975559
 -4.62227638]
b = [23.70362149]
```

In [26]:
```
import math
test_temp = X_test.drop("PRICE", axis = 1, inplace = False)
test_std = StandardScaler().fit_transform(test_temp)
test_data = pd.DataFrame(test_std, columns = columnNames)
test_labels = Y_test
y_predicted = []

for i in range(102):
    test_i = 0
    test_i = np.dot(weight, test_data.iloc[i]) + b[0]  #making prediction by using min values of weight obtained from SGD
    y_predicted.append(test_i)

y_true = []
for i in range(102):
    y_true.append(test_labels.iloc[i])
```

In [27]:
```
d1 = {'True Labels': Y_test, 'Predicted Labels': y_predicted}
df1 = pd.DataFrame(data = d1)
df1
```

Out[27]:

	True Labels	Predicted Labels
307	28.2	33.574712
385	7.2	9.976670
36	20.0	22.681121
380	10.4	23.861470
409	27.5	23.335253
414	7.0	-0.529739
178	29.9	32.621376
341	32.7	32.601284
302	26.4	28.449411
86	22.5	21.823519
308	22.8	31.300523
276	33.2	39.287680
500	16.8	21.771495
79	20.3	22.598499
214	23.7	7.426240
476	16.7	23.185484
120	22.0	22.459707
83	22.9	25.998738
150	21.5	24.149239
209	20.0	19.805452
386	10.5	8.650260
39	30.8	31.750179
260	33.8	36.041398

	True Labels	Predicted Labels
117	19.2	25.225483
191	30.5	31.497098
70	24.2	24.933699
28	18.4	22.795985
327	22.2	20.232604
359	22.6	23.134161
200	32.9	32.274996
...	...	...
420	16.7	24.018745
220	26.7	37.112744
183	32.5	32.703507
323	18.5	21.005108
317	19.8	19.302545
468	19.1	19.493337
97	38.7	38.107872
319	21.0	22.306002
141	14.4	3.929432
113	18.7	21.920684
484	20.6	20.825408
177	24.6	30.268484
127	16.2	17.319076
229	31.5	31.007247
344	31.2	30.497529
61	16.0	21.420041
128	18.0	21.806511
238	23.7	28.633456

	True Labels	Predicted Labels
138	13.3	15.613109
354	18.2	17.560080
121	20.3	23.625482
75	21.4	24.724778
358	22.7	28.895073
457	13.5	16.890481
168	23.8	28.485455
171	19.1	26.148232
384	8.8	4.897493
123	17.3	16.586335
192	36.4	34.403742
351	24.1	24.660269

102 rows × 2 columns

In [28]:
```
Mean_Sq_Error = mean_squared_error(y_true, y_predicted)
Mean_Sq_Error
```

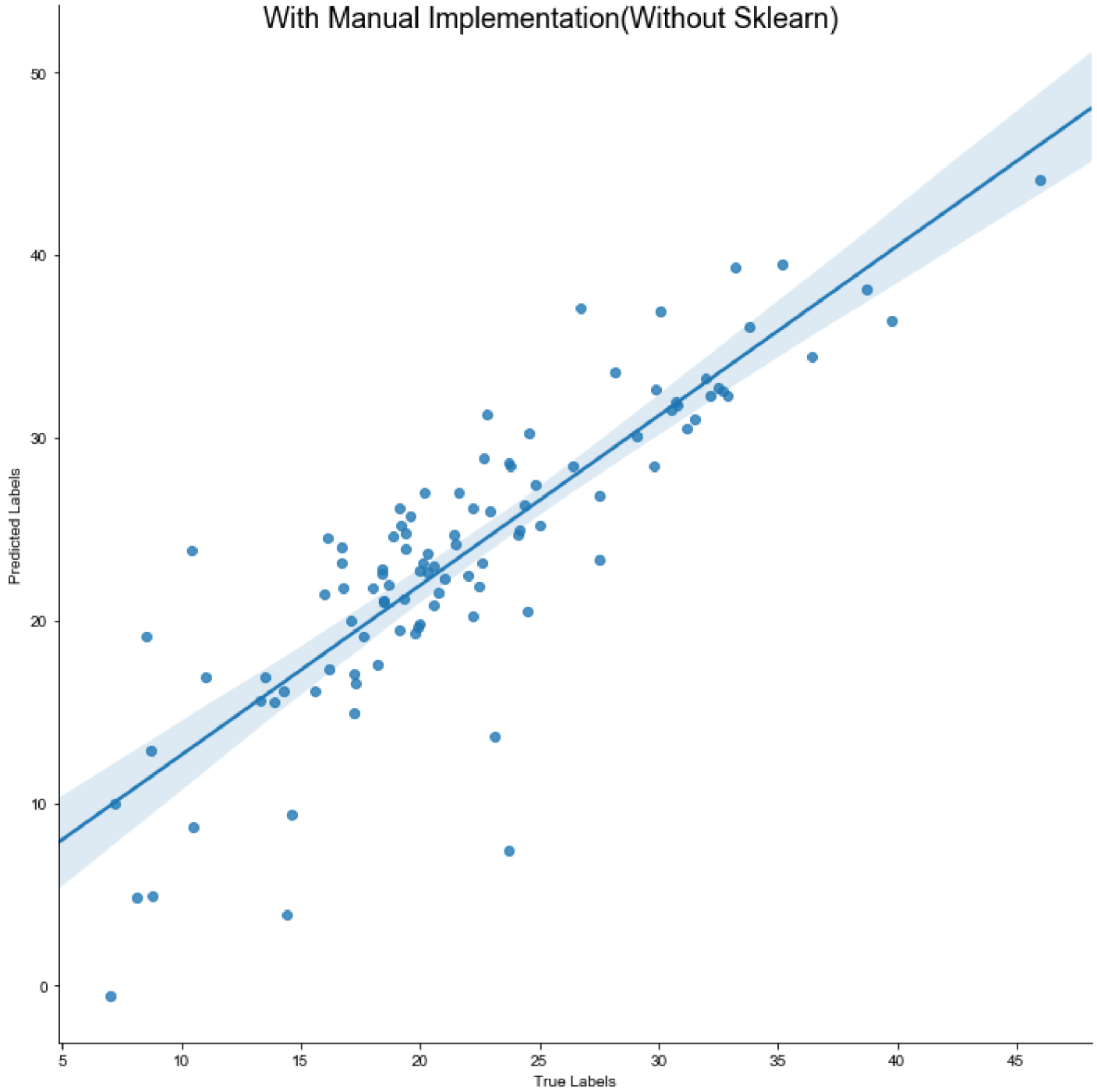
Out[28]:
```
21.186227759904064
```

In [29]:
```
lm1 = sns.lmplot(x="True Labels", y="Predicted Labels", data = df1, size = 10)

fig1 = lm1.fig

fig1.suptitle("With Manual Implementation(Without Sklearn)", fontsize=18)

sns.set(font_scale = 1.5)
```


With Manual Implementation(Without Sklearn)
Predicted Labels
True Labels
0
10
20
30
40
50
5
10
15
20
25
30
35
40
45

In [30]:
```
X_temp = X_train.drop("PRICE", axis = 1, inplace = False)
X_std = StandardScaler().fit_transform(X_temp)
X = pd.DataFrame(X_std, columns = columnNames)
Y = Y_train

X_test_temp = X_test.drop("PRICE", axis = 1, inplace = False)
X_test_std = StandardScaler().fit_transform(X_test_temp)
X_te = pd.DataFrame(X_test_std, columns = columnNames)
Y_te = Y_test

clf = SGDRegressor(shuffle = False, learning_rate= 'invscaling', n_iter = 2500)
clf.fit(X, Y)

Y_pred = clf.predict(X_te)

print("Weight = "+str(clf.coef_))
print("Y Intercept = "+str(clf.intercept_))
```

```
Weight = [-0.89269428  1.00193127  0.13084557  0.60707741 -2.18656679  2.65855319
  0.48883977 -3.1378251   3.06195059 -2.31933488 -2.2108428   0.98680097
 -4.40275391]
Y Intercept = [22.69923301]

C:\Users\GauravP\Anaconda3\lib\site-packages\sklearn\linear_model\stochastic_gradient.py:117: DeprecationWarning: n_ite
r parameter is deprecated in 0.19 and will be removed in 0.21. Use max_iter and tol instead.
  DeprecationWarning)
```

In [31]:
```
d2 = {'True Labels': Y_te, 'Predicted Labels': Y_pred}
df2 = pd.DataFrame(data = d2)
df2
```

Out[31]:

	True Labels	Predicted Labels
307	28.2	34.625922
385	7.2	8.343819
36	20.0	23.316409
380	10.4	17.438339
409	27.5	20.622426
414	7.0	-4.672888
178	29.9	33.368859
341	32.7	31.891682
302	26.4	29.890827
86	22.5	22.931960
308	22.8	30.479532
276	33.2	36.848141
500	16.8	21.261716
79	20.3	23.172265
214	23.7	9.750177
476	16.7	21.598159
120	22.0	22.643716
83	22.9	26.195696
150	21.5	21.729502
209	20.0	17.517960
386	10.5	6.814786
39	30.8	32.455154
260	33.8	36.925601

	True Labels	Predicted Labels
117	19.2	25.052271
191	30.5	31.687539
70	24.2	25.651552
28	18.4	20.505749
327	22.2	19.798277
359	22.6	20.066619
200	32.9	31.447576
...	...	...
420	16.7	20.724189
220	26.7	34.896699
183	32.5	33.364668
323	18.5	20.529674
317	19.8	19.080668
468	19.1	17.932330
97	38.7	37.809138
319	21.0	22.071387
141	14.4	3.041505
113	18.7	21.783646
484	20.6	19.919586
177	24.6	31.086678
127	16.2	15.453201
229	31.5	32.501553
344	31.2	29.492981
61	16.0	19.817923
128	18.0	19.424246
238	23.7	29.507171

	True Labels	Predicted Labels
138	13.3	13.811254
354	18.2	14.232612
121	20.3	23.421829
75	21.4	24.833043
358	22.7	22.931203
457	13.5	12.468762
168	23.8	27.986559
171	19.1	25.952486
384	8.8	3.198285
123	17.3	16.656538
192	36.4	34.391115
351	24.1	21.243552

102 rows × 2 columns

In [32]:
```
Mean_Sq_Error = mean_squared_error(Y_te, Y_pred)
Mean_Sq_Error
```

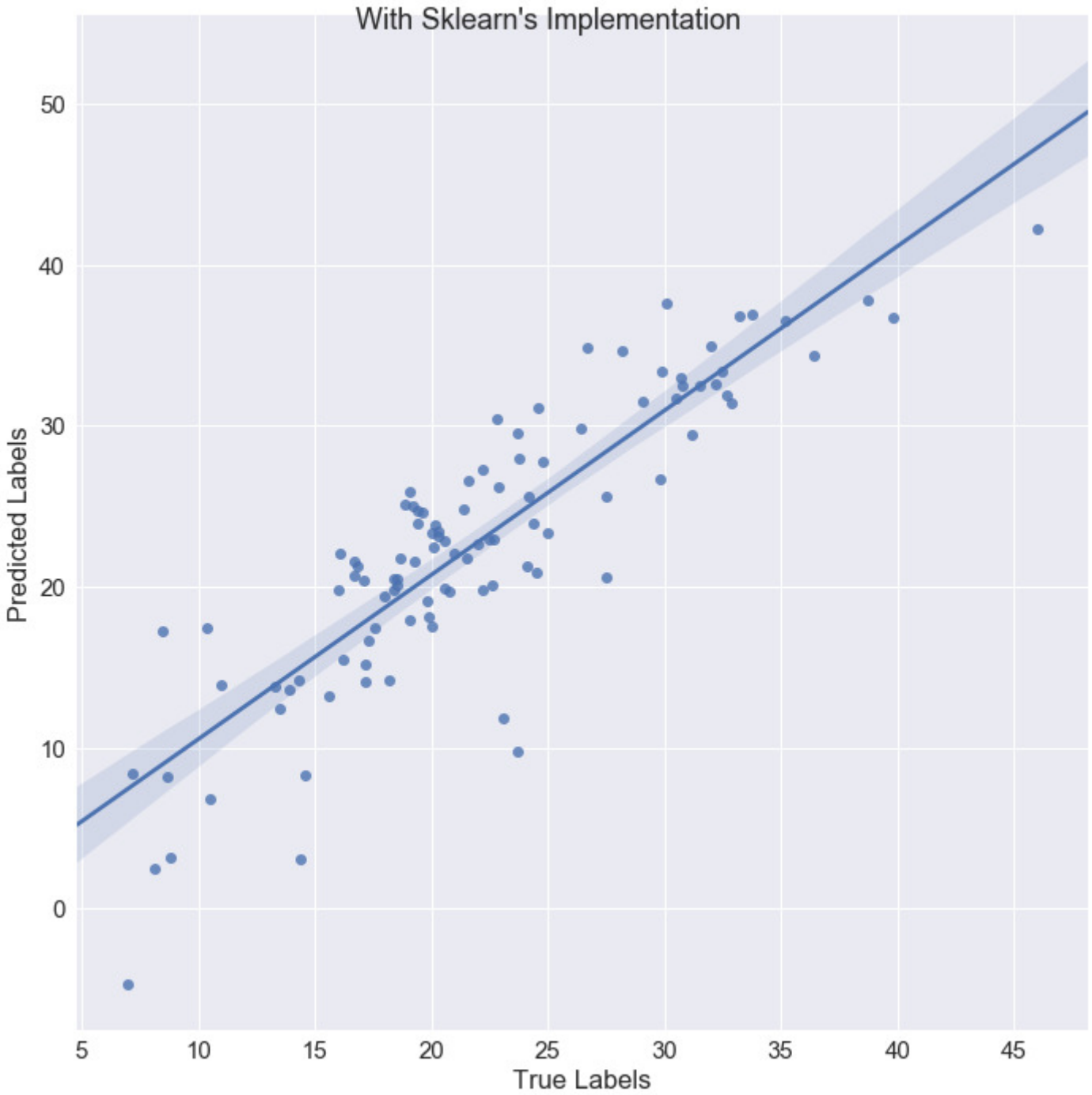
Out[32]: 18.601333691948366

In [33]:
```
lm2 = sns.lmplot(x="True Labels", y="Predicted Labels", data = df2, size = 10)

fig2 = lm2.fig

# Add a title to the Figure
fig2.suptitle("With Sklearn's Implementation", fontsize=18)

sns.set(font_scale = 1.5)
```


With Sklearn's Implementation
Predicted Labels
True Labels
50
40
30
20
10
0
5
10
15
20
25
30
35
40
45

Final Verdict:

Mean Square Error

Manual Implementation: 21.186
Sklearn Implementation: 18.60