Linear Regression - Stochastic Gradient Descent

In [51]:

```
import warnings
warnings.filterwarnings("ignore")
from sklearn.datasets import load_boston
from random import seed
from random import randrange
from csv import reader
from math import sqrt
from sklearn import preprocessing
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from prettytable import PrettyTable
from sklearn.linear_model import SGDRegressor
from sklearn import preprocessing
from sklearn.metrics import mean_squared_error
```

In [52]:

```
data=load_boston()
```

In [53]:

```
print(data.DESCR)
```

```
.. _boston_dataset:

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

**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.
https://archive.ics.uci.edu/ml/machine-learning-databases/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.

.. topic:: References

   - Belsley, Kuh & Welsch, 'Regression diagnostics: Identifying Influential Data and Sources of C
ollinearity', Wiley, 1980. 244-261.
   - Quinlan,R. (1993). Combining Instance-Based and Model-Based Learning. In Proceedings on the T
enth International Conference of Machine Learning, 236-243, University of Massachusetts, Amherst.
Morgan Kaufmann.
```

Objective:

- Here the objective of this analysis is to predict the house price

In [54]:

```
# Feature names

print(data.feature_names)
```

```
['CRIM' 'ZN' 'INDUS' 'CHAS' 'NOX' 'RM' 'AGE' 'DIS' 'RAD' 'TAX' 'PTRATIO'
 'B' 'LSTAT']
```

In [55]:

```
# loading to DataFrame

boston_data=pd.DataFrame(data.data,columns=data.feature_names)
```

In [56]:

```
boston_data.shape
```

Out[56]:

```
(506, 13)
```

In [57]:

```
# Adding label to the dataframe

boston_data["Price"]=data.target
```

In [58]:

```
boston_data.head()
```

Out[58]:

	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

Splitting the data into Train and Test

In [59]:

```
X=boston_data.drop("Price",axis=1)
Y=boston_data["Price"]
```

In [60]:

```
# References
# https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.train_test_split.html

from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(X,Y,test_size=0.2,random_state=12)
```

In [61]:

```
print("Split ratio")
print('-'*50)
print('Train dataset:',len(x_train)/len(X)*100,'%\n','size:',len(x_train))

print('Test dataset:',len(x_test)/len(X)*100,'%\n','size:',len(x_test))
```

```
Split ratio
--------------------------------------------------
Train dataset: 79.84189723320159 %
 size: 404
Test dataset: 20.158102766798418 %
 size: 102
```

In [62]:

```
print("train data shape (x_train,y_train)")
print("(",x_train.shape,",",y_train.shape,")")
print("test data shape (x_test,y_test)")
print("(",x_test.shape,",",y_test.shape,")")
```

```
train data shape (x_train,y_train)
( (404, 13) , (404,) )
test data shape (x_test,y_test)
( (102, 13) , (102,) )
```

Stochastic Gradient Descent (SGD) Algorithm implementation

In [63]:

```
# Data standardization
# References
# https://scikit-learn.org/stable/modules/generated/sklearn.preprocessing.StandardScaler.html

from sklearn.preprocessing import StandardScaler
from tqdm import tqdm
data_std=StandardScaler()
x_train_std=data_std.fit_transform(x_train)
x_test_std=data_std.transform(x_test)
```

SGD Working Principle:

- Randomly choose w and b
- Initialize the learning rate and iteration
- Pick a random set of k points for every iteration, where $1≤k≥n$
- Update gradient for each iteration
- Run a loop untill obtain the minimum w and b

Creating Function for SGD

In [64]:

In [64]:

```
#Citations:
# https://www.appliedaicourse.com/course/applied-ai-course-online/lessons/function-arguments/
# https://www.geeksforgeeks.org/functions-in-python/
# https://www.geeksforgeeks.org/g-fact-41-multiple-return-values-in-python/

# Reference for To Generate the random values
# https://docs.scipy.org/doc/numpy/reference/generated/numpy.random.randint.html
```

In [65]:

```
# References To generate the the random w and b using Normal Distribution
# https://docs.scipy.org/doc/numpy-1.14.0/reference/generated/numpy.random.normal.html

# References To produce the same set of random values in the Normal distribution
# https://stackoverflow.com/questions/21494489/what-does-numpy-random-seed0-do
# https://docs.scipy.org/doc/numpy/reference/generated/numpy.random.seed.html

# References for SGD Regeressor Implementation
# https://towardsdatascience.com/gradient-descent-in-python-a0d07285742f
# http://mccormickml.com/2014/03/04/gradient-descent-derivation/
# https://machinelearningmastery.com/implement-linear-regression-stochastic-gradient-descent-scrat
ch-python/
# https://www.pyimagesearch.com/2016/10/17/stochastic-gradient-descent-sgd-with-python/
# https://github.com/PushpendraSinghChauhan/SGD-Linear-Regression/blob/master/
# https://medium.com/@lachlanmiller_52885
  #/machine-learning-week-1-cost-function-gradient-descent-and-univariate-linear-regression-8f5fe6
9815fd
# https://scikit-learn.org/stable/modules/sgd.html.
# https://www.kaggle.com/tentotheminus9/linear-regression-from-scratch-gradient-descent

# Reference for tqdm
# https://pypi.org/project/tqdm/
```

In [66]:

```
# Function for creating a k sample for each iteration:

def k_sample(**para):

    k_sample_x=[]
    k_sample_y=[]

    sample=np.random.randint(0,354,size=para["sample_size"])

    fi=para["train_data"]
    la=para["train_label"].values

    for i in sample:

        a= list(fi[i])
        b=la[i]

        k_sample_x.append(a)
        k_sample_y.append(b)

    k_sample_x=np.asarray(k_sample_x)
    k_sample_y=np.asarray(k_sample_y)
    k_sample_y=np.reshape(k_sample_y,(para["sample_size"],1))

    return k_sample_x,k_sample_y
```

In [67]:

```
# Fuction for finding optimal w , b, mse and cost_list Using Stochastic Gradient Descent Optimizat
ion (SGD) Algorithm.

def optimal_w_b(**para):

    # Initializing

    size_w = para["train_data"].shape[1]
    np.random.seed(20)
    w = np.random.normal(loc=0,scale=1,size=size_w)
```

```
    w = np.random.normal(loc=0,scale=1,size=size_w)
    w = np.reshape(w,(1,size_w))
    b=float(np.random.normal(loc=0,scale=1,size=1))
    r=0.001

    w_list = []
    b_list = []
    cost_list = []
    value=para["iteration"]

    # Loop for getting a optimul w and b using n iterations

    for i in tqdm(range(0,value)):

        # k samples produces for each iteration

        k_sample_x,k_sample_y=k_sample(sample_size=para["sample_size"],train_data=para["train_data"
],\
                                       train_label=para["train_label"])

        n= k_sample_y.shape[0]


        # Initialization to store the values

        grad_w = np.zeros((1,size_w))
        grad_b = 0
        cost = 0

        # Loop for produce the error and cost fuction

        for x,y in zip(k_sample_x,k_sample_y):

            x=np.reshape(x,(1,size_w))

            y=float(y)

            pred = np.dot(x,w.T) + b

            error = y - pred

            grad_w = grad_w + (x * error)

            grad_b = grad_b + (error)

            cost = cost + ((error)**2)

        dl_dw = (-2/n) * grad_w

        dl_db = (-2/n) * grad_b

        cost_value = (1/n) * (cost)

        w = w - ( r * dl_dw)

        b = b - (r * dl_db)

        # Storing w and b which will get each iterations

        w_list.append(w)
        b_list.append(b)
        cost_list.append(float(cost_value))

    # Optimal w,b,mse

    w_optimum=np.asarray(w_list[-1])
    w_optimum= w_optimum[0]
    b_optimum =np.asarray(b_list[-1])
    b_optimum = float(b_optimum)
    mse = np.asarray(cost_list[-1])
    mse=float(mse)

    # Function Return values (w,b,mse,cost_list)

    return w_optimum,b_optimum,mse,cost_list
```

In [68]:

```python
# Fuction for Predict the test data using optimal w,b

def SGD_Regressor_custom(**para):

    # list to store the predicted value

    pred_list =[]
    cost=0
    w=para["optimal_w"]
    b=para["optimal_b"]

    # loop for Predict the test data using optimal w and b

    for x,y in zip(para["test_data"],para["test_label"]):

        size = para["test_data"].shape[1]

        n= para["test_data"].shape[0]

        x=np.reshape(x,(1,size))

        y=float(y)

        pred = np.dot(x,w.T) + b

        error = y - pred

        # MSE

        cost = cost + ((error)**2)

        pred_list.append(float(pred))

    mse = (1/n) * (cost)

    predict_value = np.asarray(pred_list)

    # Return predicted values

    return predict_value,float(mse)
```

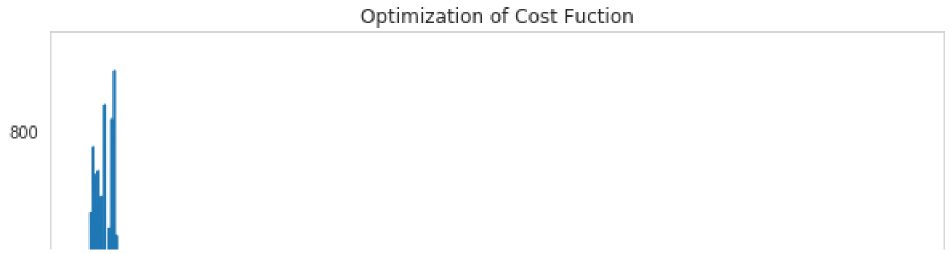
In [69]:

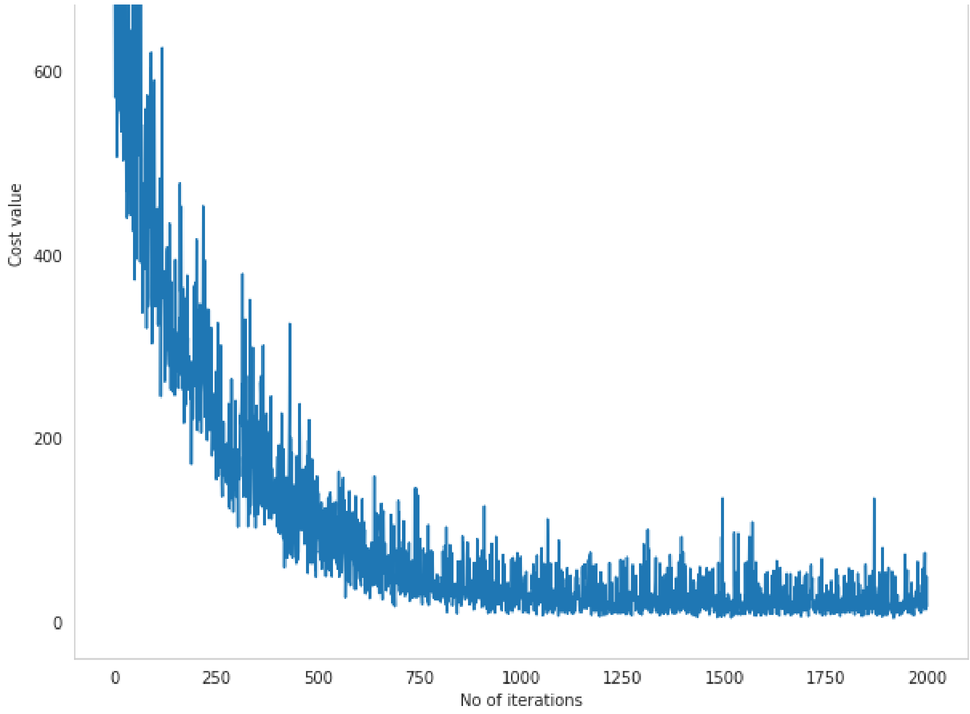
```python
# Finding optimal w,b,mse and cost_list

w_optimum,b_optimum,mse_train,cost_list=optimal_w_b(iteration=2000,sample_size=20,train_data=x_tra
in_std,train_label=y_train)
```

```
100%|██████████| 2000/2000 [00:00<00:00, 4570.24it/s]
```

In [70]:

```python
# Plotting cost values for each iteration

plt.close()
plt.figure(figsize=(10,10))
plt.plot(range(0,2000),cost_list)
plt.grid()
plt.xlabel("No of iterations")
plt.ylabel("Cost value")
plt.title("Optimization of Cost Fuction")
plt.show()
```





Observation:

- If the number of iteration increases, The MSE (Cost) reduces.

In [71]:

```
# Predict the test data using manually optimized w and b

y_custom,mse=SGD_Regressor_custom(optimal_w=w_optimum,optimal_b=b_optimum,test_data=x_test_std,tes
t_label=y_test)
```

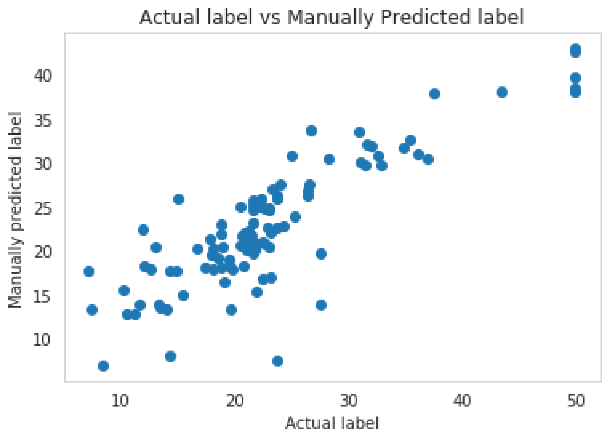
In [72]:

```
print(" the Optimal weight vector of manually implemented SGD")
print("="*125)
print(w_optimum)
print(" ")
print(" the Optimal y intercept of manually implemented SGD")
print("="*125)
print(b_optimum)
print(" ")
print("The mse value of manually implemented SGD")
print("="*125)
print(mse)
```

```
 the Optimal weight vector of manually implemented SGD
=============================================================================================
======================
[-0.77812515  0.40610261 -0.27094832  0.98905431 -1.40834991  2.89629074
  0.64666167 -2.14462645  1.23314931 -0.4524809  -1.79102283  0.73413303
 -4.31336998]

 the Optimal y intercept of manually implemented SGD
=============================================================================================
======================
22.035944435479514

The mse value of manually implemented SGD
=============================================================================================
======================
21.770055179819852
```

In [73]:

```
# Plot for actual values vs manually predicted values

plt.close()
plt.scatter(y_test,y_custom)
plt.grid()
plt.title("Actual label vs Manually Predicted label")
plt.xlabel("Actual label")
plt.ylabel("Manually predicted label")
plt.show()
```

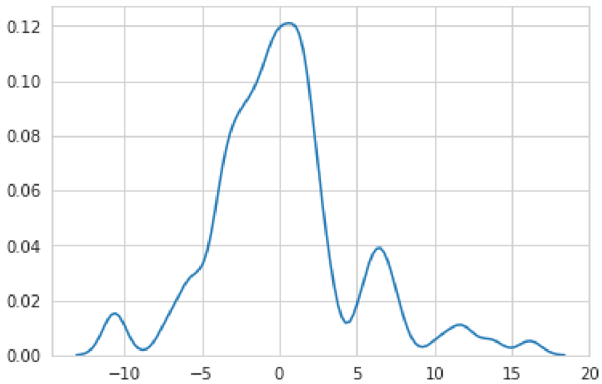


In [74]:

```
delta = y_test - y_custom
```

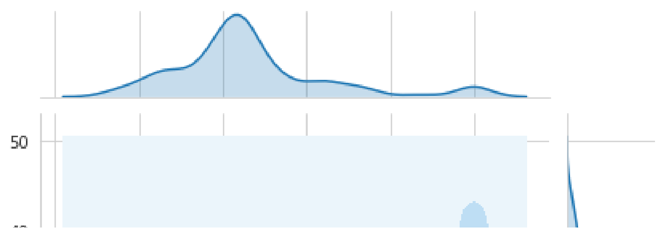
In [75]:

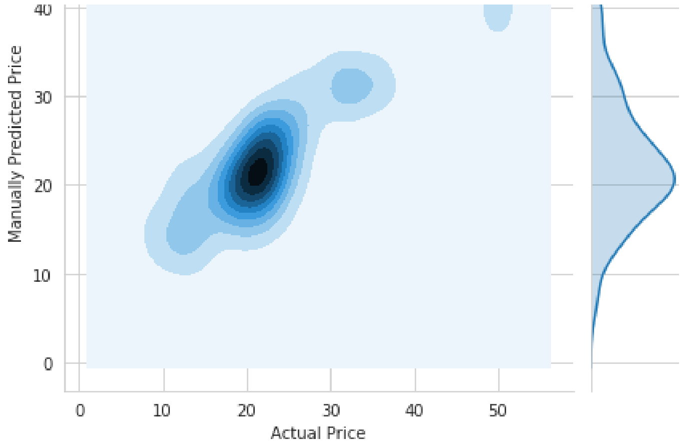
```
# Plotting the error difference (delta)
import seaborn as sns
plt.close()
sns.set_style("whitegrid")
sns.kdeplot(np.array(delta),bw=.75)
plt.show()
```



In [76]:

```
plt.close()
sns.set_style("whitegrid")
fig=sns.jointplot(x=y_test,y=y_custom,kind="kde")
fig.set_axis_labels('Actual Price', 'Manually Predicted Price')
plt.show()
```





Observation:

- Maximum number of actual and predicted price points lie between 15 to 35

Implementation of Stochastic Gradient Descent (SGD) Algorithm using Sklearn

In [77]:

```
from sklearn.linear_model import SGDRegressor
from sklearn.metrics import mean_squared_error

# Fitting a data to find optimal w and b

model = SGDRegressor(max_iter=2000)
model.fit(x_train_std,y_train)
w_sklearn=model.coef_
b_sklearn=model.intercept_
```

In [78]:

```
# Predicting using sklearn model

y_sklearn = model.predict(x_test_std)
mse_sklearn = mean_squared_error(y_test,y_sklearn)
```

In [79]:

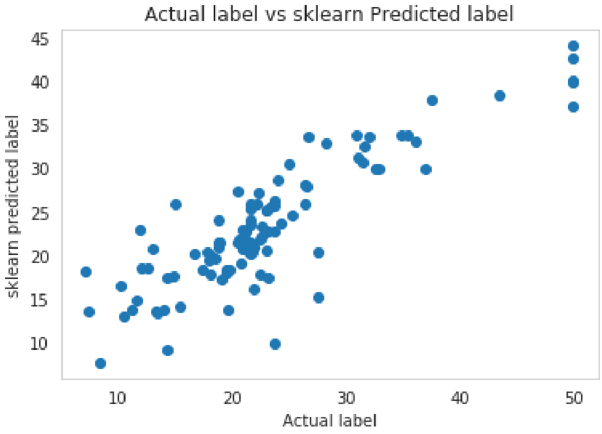
```
print(" the Optimal weight vector of sklearn implemented SGD")
print("="*125)
print(w_sklearn)
print(" ")
print(" the Optimal y intercept of sklearn implemented SGD")
print("="*125)
print(b_sklearn)
print(" ")
print("The mse value of sklearn implemented SGD")
print("="*125)
print(mse_sklearn)
```

```
 the Optimal weight vector of sklearn implemented SGD
=============================================================================================================================
[-0.89026351  1.09447669  0.22292746  0.79080819 -2.07301744  2.5906061
  0.4253591  -3.0260349   2.83140261 -2.26526786 -1.74512239  0.82982324
 -4.10515481]
 
 the Optimal y intercept of sklearn implemented SGD
=============================================================================================================================
[ 22.39845869]
 
The mse value of sklearn implemented SGD
=====================================================================================================
```

```
=======================
20.6974994652
```

In [80]:

```python
# Plot for actual values vs sklearn predicted values

plt.close()
plt.scatter(y_test,y_sklearn)
plt.title("Actual label vs sklearn Predicted label")
plt.xlabel("Actual label")
plt.ylabel("sklearn predicted label")
plt.grid()
plt.show()
```

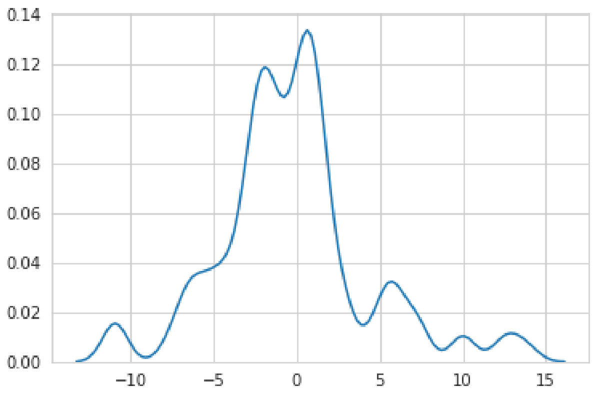


In [81]:

```python
delta= y_test - y_sklearn
```

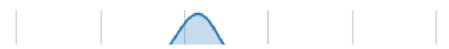
In [82]:

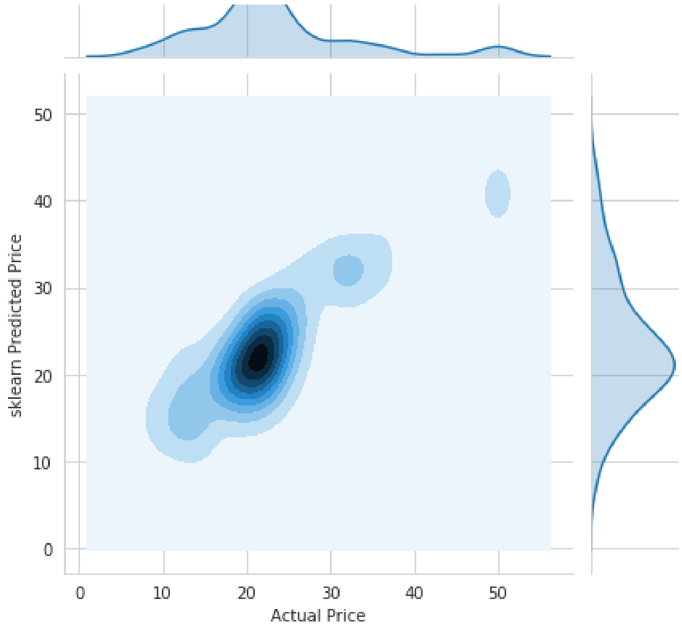
```python
# Plotting the error difference (delta)

plt.close()
sns.set_style("whitegrid")
sns.kdeplot(np.array(delta),bw=.75)
plt.show()
```



In [83]:

```python
plt.close()
sns.set_style("whitegrid")
fig=sns.jointplot(x=y_test,y=y_sklearn,kind="kde")
fig.set_axis_labels('Actual Price', 'sklearn Predicted Price')
plt.show()
```



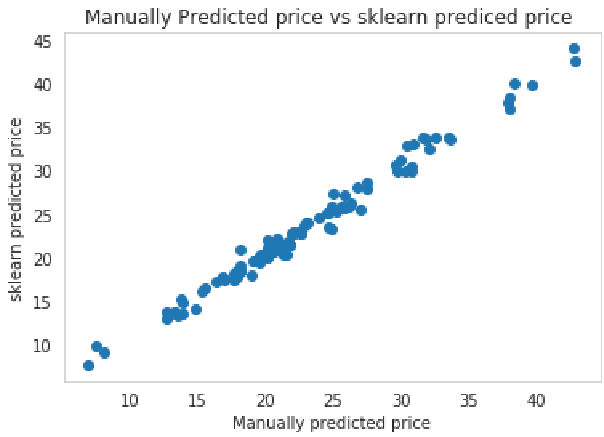


Observation:

- Maximum number of actual and predicted price points lie between 15 to 35

In [84]:

```
plt.close()
plt.scatter(y_custom,y_sklearn)
plt.grid()
plt.title("Manually Predicted price vs sklearn prediced price ")
plt.xlabel("Manually predicted price")
plt.ylabel("sklearn predicted price")
plt.show()
```



Observation:

- The predicted price from sklearn's implentation is almost the same as the previous one

Comparing the values of both implementations using PrettyTable

In [85]:

```
# References
# http://zetcode.com/python/prettytable/

from prettytable import PrettyTable
```

In [86]:

```python
x=PrettyTable()

print("Weight vector Comparision of Both Own and sklearn SGD")
print("="*125)
print(" ")
x.add_column("w_number",[1,2,3,4,5,6,7,8,9,10,11,12,13])
x.add_column("Own implemented SGD",w_optimum)
x.add_column("Sklearn implemented SGD",w_sklearn)
print(x)
print(" ")

y=PrettyTable()
print("Intercept term Comparision of Both Own and sklearn SGD")
print("="*125)
print(" ")
y.field_names = ["Own implemented SGD","Sklearn implemented SGD"]
y.add_row([b_optimum,float(b_sklearn)])
print(y)
print(" ")

z=PrettyTable()
print("Mean Squared Error (MSE) Comparision of Both Own and sklearn SGD")
print("="*125)
print(" ")
z.field_names = ["Own implemented SGD","Sklearn implemented SGD"]
z.add_row([mse,mse_sklearn])
print(z)
```

```
Weight vector Comparision of Both Own and sklearn SGD
=============================================================================================================================

+----------+---------------------+-------------------------+
| w_number | Own implemented SGD | Sklearn implemented SGD |
+----------+---------------------+-------------------------+
|    1     |   -0.778125145726   |     -0.890263508549     |
|    2     |    0.406102605601   |      1.09447669092      |
|    3     |   -0.270948320162   |      0.222927458718     |
|    4     |    0.989054307482   |      0.790808188879     |
|    5     |    -1.40834990997   |      -2.07301744028     |
|    6     |    2.89629073637    |      2.59060610495      |
|    7     |     0.6466616709    |      0.425359102891     |
|    8     |    -2.14462644854   |      -3.02603490068     |
|    9     |    1.23314930667    |      2.83140261256      |
|    10    |   -0.452480897221   |      -2.26526786366     |
|    11    |    -1.7910228284    |      -1.74512238906     |
|    12    |    0.734133029915   |      0.829823236114     |
|    13    |    -4.31336998473   |      -4.10515480793     |
+----------+---------------------+-------------------------+

Intercept term Comparision of Both Own and sklearn SGD
=============================================================================================================================

+---------------------+-------------------------+
| Own implemented SGD | Sklearn implemented SGD |
+---------------------+-------------------------+
|  22.035944435479514 |    22.39845869138315    |
+---------------------+-------------------------+

Mean Squared Error (MSE) Comparision of Both Own and sklearn SGD
=============================================================================================================================

+---------------------+-------------------------+
| Own implemented SGD | Sklearn implemented SGD |
+---------------------+-------------------------+
|  21.770055179819852 |      20.6974994652      |
+---------------------+-------------------------+
```