Gradient Descent implementation from the scratch

In [0]:

```
import warnings
warnings.filterwarnings("ignore")
from sklearn.datasets import load_boston
from random import seed
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean_squared_error
```

Loading Boston dataset

```
In [0]:
```

```
X = load_boston().data
Y = load_boston().target
```

Code implementation

In [0]:

```
# cost variable stores loss value in each iteration, useful for ploting loss v/s iterat
ions
cost=[]
class GradientDescent:
    def __init__(self, learning_rate, n_iter):
        self.learning_rate = learning_rate
        self.n_iter = n_iter
    def fit(self, X, Y):
        Y=Y.reshape(-1,1)
        # standardize the data
        X = self.normalize(X)
        N= X.shape[0]
        np.random.seed(28)
        # Initialise random weights.
        W = np.random.normal(0,1,X.shape[1]).reshape(-1,1) #13*1
        # Initialize random value of Intercept
        b = np.random.normal(0,1,1)[0]
        learning_rate= self.learning_rate
        for iter_ in range(self.n_iter):
            #calculate gradients
            dLw = (-2/N)*np.matmul(X.T, (Y-np.matmul(X,W)-b))
            dLb = (-1/N)*(Y-np.dot(X,W)-b) # intercept should be scalar
            W = W - (learning_rate * dLw)
            b = b - (learning_rate * sum(dLb))
            error = mean_squared_error(Y, np.dot(X,W)+b)
            cost.append(error)
            #print("iter : {0}, error :{1} , intercept= {2}".format(iter_+1, error, b))
        self.coef_= W
        self.intercept_= b
    def normalize(self, X):
        sc = StandardScaler()
        X = sc.fit transform(X)
        return X
    def predict(self, X):
        X=self.normalize(X)
        return np.dot(X,self.coef_)+self.intercept_
```

Comparision of results

Scratch code's Gradient Descent

```
In [15]:
```

```
#learing rate
learning_rate=0.01
#no of iterations
n iter=500
gd = GradientDescent(learning_rate=learning_rate, n_iter=n_iter)
gd.fit(X,Y)
pred= gd.predict(X)
print("Weights: ", gd.coef_," & Intercept: ", gd.intercept_)
print("MSE error : ", mean_squared_error(Y, gd.predict(X)) )
Weights: [[-0.76121935]
 [ 0.88472784]
 [-0.29277136]
 [ 0.74502663]
 [-1.52786238]
 [ 2.87621452]
 [-0.10634081]
 [-2.8062878]
 [ 1.36976216]
 [-0.8641931]
 [-1.88936034]
 [ 0.86063672]
 [-3.67940582]] & Intercept: [22.37308921]
MSE error: 22.207430796607607
```

LinearRegression from Sklearn

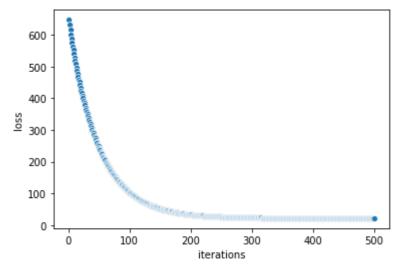
```
In [8]:
```

Gradient Descent plot-Loss v/s Iterations

In [16]:

```
import seaborn as sns
import matplotlib.pyplot as plt

sns.scatterplot(range(1,n_iter+1), cost)
plt.xlabel("iterations")
plt.ylabel("loss")
plt.show()
```



Conclusion

We can enhance the performance by adding more hyper-parameters.

Refer: https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.SGDRegressor.html)

In [17]:

```
from prettytable import PrettyTable
pt = PrettyTable(["","GradientDescent","LinearRegression"])
pt.add_row(["error(MSE)", 21.98, 21.89])
pt.add_row(["intercept", 22.37, 22.53])
pt.add_row(["n_iter", 500, "-"])
pt.add_row(["learning_rate", 0.01, "-"])
print(pt)
```

| + | | |
|-----------------------|-----------------|------------------|
| į | GradientDescent | LinearRegression |
| error(MSE) | 21.98 | 21.89 |
| intercept n_iter | 22.37 500 | 22.53 - |
| learning_rate | 0.01 | - [|

```
In [0]:
```