Implement SGD

January 2, 2019

1 Importing required libraries

```
In [0]: 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
        from sklearn.linear_model import LinearRegression
        from sklearn.linear_model import SGDRegressor
        from sklearn.base import BaseEstimator
        from sklearn.preprocessing import StandardScaler
```

2 Loading the dataset

```
In [0]: X = load_boston().data
        y = load_boston().target
```

2.1 Train-Test Split

```
In [0]: from sklearn.model_selection import train_test_split
        X_train,X_test,y_train,y_test = train_test_split(X, y, test_size = 0.33, random_state
```

```
In [0]: sc = StandardScaler()
        X_train = sc.fit_transform(X_train)
        X_test = sc.transform(X_test)
```

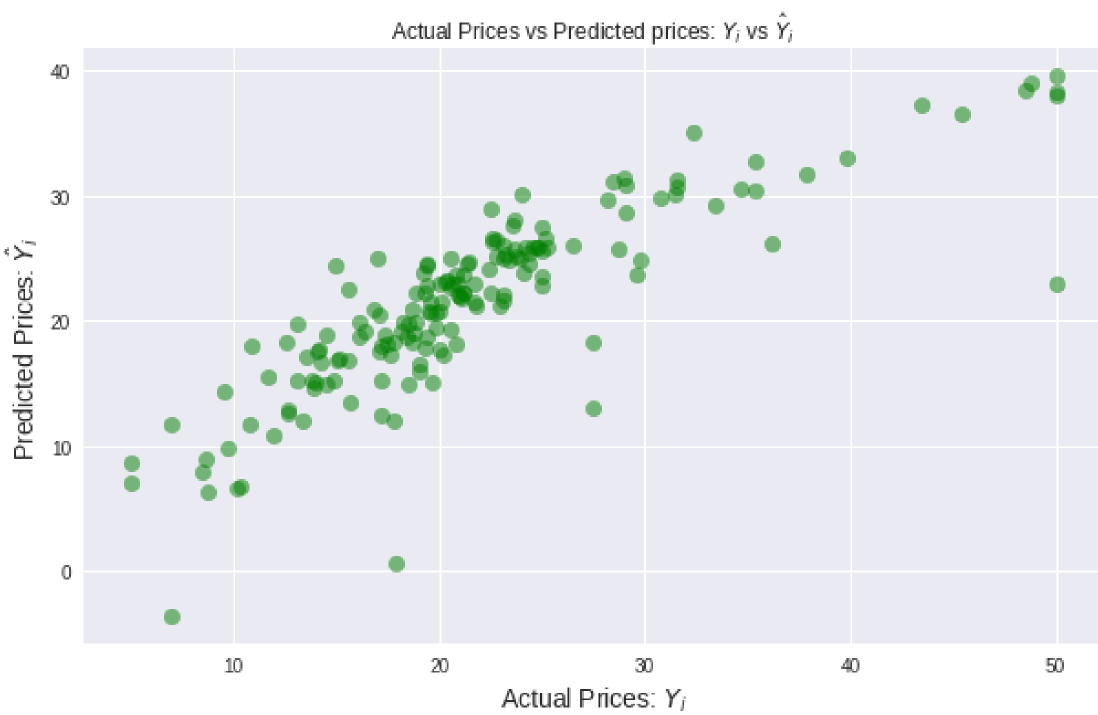
2.2 Using Sklearn's SGD Regressor model.

```
In [11]: sgd = SGDRegressor(penalty='l2', alpha=0.15, max_iter=2000)
         sgd.fit(X_train,y_train)
```

```
Out[11]: SGDRegressor(alpha=0.15, average=False, early_stopping=False, epsilon=0.1,
                eta0=0.01, fit_intercept=True, l1_ratio=0.15,
                learning_rate='invscaling', loss='squared_loss', max_iter=2000,
                n_iter=None, n_iter_no_change=5, penalty='l2', power_t=0.25,
                random_state=None, shuffle=True, tol=None, validation_fraction=0.1,
                verbose=0, warm_start=False)
```

```
In [0]: y_pred =  sgd.predict(X_test)
```

```
In [13]: plt.figure(figsize=(10,6))
         plt.rc('axes', labelsize=14)
         plt.scatter(y_test,y_pred,s=75,color="g",alpha=0.5)
         plt.xlabel("Actual Prices: $Y_i$")
         plt.ylabel("Predicted Prices: $\hat{Y}_i$")
         plt.title("Actual Prices vs Predicted prices: $Y_i$ vs $\hat{Y}_i$")
         plt.show()
```




```
In [23]: print(mean_squared_error(y_test, y_pred))
```

```
21.918527804270198
```

2.2.1 The MSE obtained after using Sklearn's SGDRegressor = 21.918527804270198

2.3 Creating a custom SGD Regressor.

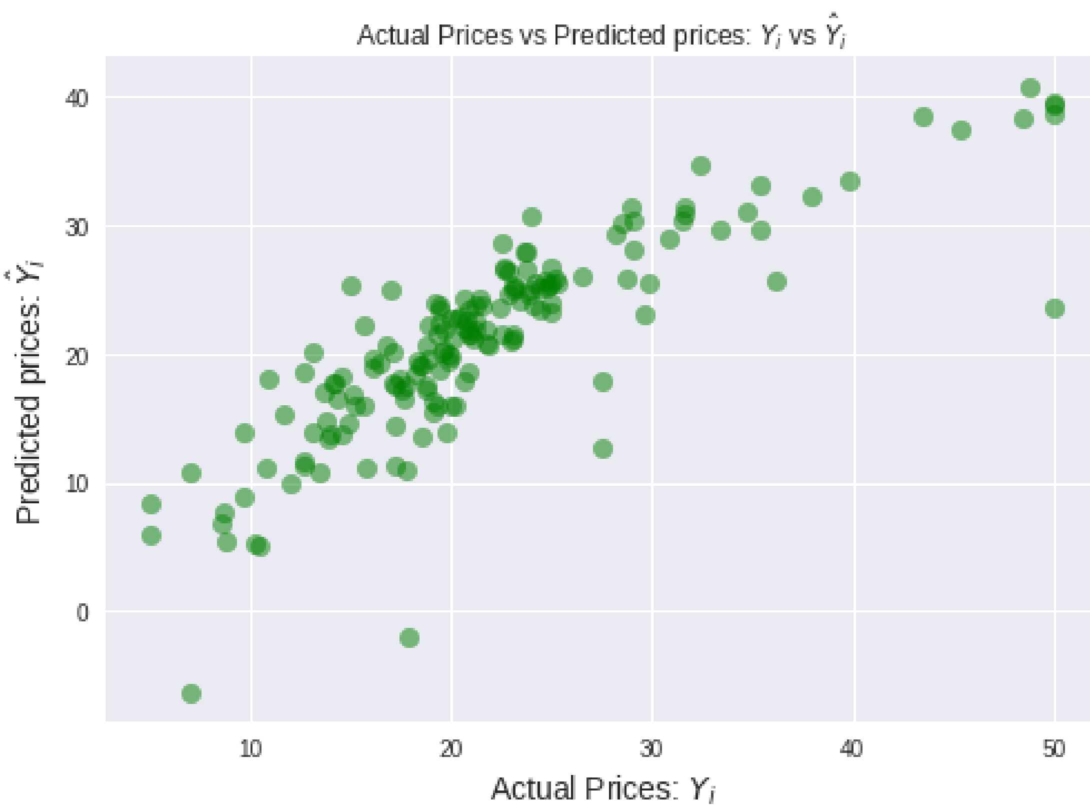
In [0]:
```
class SGDRegressor(BaseEstimator):
    """
    Custom stochastic gradient descent
    algorithm for linear regression
    """
    def __init__(self,max_iter=1000, alpha=0.0001, tol=0.0001, batch_size=50):
        self.max_iter = max_iter
        self.alpha = alpha
        self.tol = tol
        self.batch_size = batch_size

        self.coef_ = None
        self.intercept_ = None

        # for debugging
        self.total_errors = []
        self.sample_errors = []
        self.coef_diffs = []
        self.intercept_diffs = []

    def fit(self, X, y):
        X = np.array(X)
        y = np.array(y)

        rows, features = X.shape

        # Initialize coef and intercept
        self.coef_ = np.zeros(features)
        self.intercept_ = 0.0

        self.optimize(X, y)
        return self

    def predict(self, X):
        return X.dot(self.coef_) + self.intercept_

    def sample(self, X, y):
        """
        returns a random sample of rows
        """
        idx = np.random.randint(X.shape[0], size=self.batch_size)
        return X[idx,:], y[idx]
```

```python
def compute_rms_error(self, X, y):
    return np.sqrt(np.sum((y - self.predict(X)) ** 2) / len(X))

def optimize(self, X, y):
    """
    Optimizes the coef_ and intercept
    for lower squared errors
    """
    for i in range(1, self.max_iter + 1):

        # Save the error on whole dataset
        self.total_errors.append(self.compute_rms_error(X, y))

        # Save previous
        prev_coef = self.coef_
        prev_intercept = self.intercept_

        # Take a sample
        X_sample, y_sample = self.sample(X, y)

        # Save sample error
        self.sample_errors.append(self.compute_rms_error(X_sample, y_sample))

        pred = self.predict(X_sample)
        diff = y_sample - pred


        # compute gradients
        coef_grad = -2 * np.dot(X_sample.T, diff)
        intercept_grad = -2 * np.sum(diff)

        # update coef_ and intercept
        self.coef_ = self.coef_ - (self.alpha / i) * coef_grad
        self.intercept_ = self.intercept_ - (self.alpha / i) * intercept_grad

        # Compute diff of intercept and coef
        coef_diff = np.linalg.norm(self.coef_ - prev_coef)
        intercept_diff = self.intercept_ - prev_intercept

        # Save the difference
        self.coef_diffs.append(coef_diff)
        self.intercept_diffs.append(intercept_diff)

        # if diff is less than tolerence then terminate
        if coef_diff < self.tol and intercept_diff < self.tol:
            # Save final errors
            self.total_errors.append(self.compute_rms_error(X, y))
```

```
                    self.sample_errors.append(self.compute_rms_error(X_sample, y_sample))
                    break
```

```
In [0]: sgd2 = SGDRegressor(max_iter=10000, alpha=0.005)
        sgd2.fit(X_train,y_train)
        y_pred2 = sgd2.predict(X_test)
```

```
In [21]: plt.scatter(y_test, y_pred2,s=75,color="g",alpha=0.5)
         plt.xlabel("Actual Prices: $Y_i$")
         plt.ylabel("Predicted prices: $\hat{Y}_i$")
         plt.title("Actual Prices vs Predicted prices: $Y_i$ vs $\hat{Y}_i$")
         plt.show()
```




```
In [24]: print(mean_squared_error(y_test, y_pred2))
```

```
22.57009082723169
```

2.3.1 The MSE obtained after using Sklearn's SGDRegressor = 22.57009082723169

In [0]:
```
df = pd.DataFrame()
```

In [0]:
```
df['SGDRegressor'] = y_pred
df['Custom_SGDRegressor'] = y_pred2
```

3 Conclusion

Comparison of Mean Squared Errors

- MSE using Sklearn's SGD Regressor : 21.918527804270198
- MSE using Sklearn's Custom SGDRegressor : 22.57009082723169

It could be observed that the custom SGDregressor model performs almost as good as the Sklearn's.

3.0.1 Comparison of Weights

In [30]:
```
df.head()
```

Out[30]:

	SGDRegressor	Custom_SGDRegressor
0	27.624149	27.924287
1	35.077487	34.636783
2	17.123584	16.979961
3	25.148069	24.681857
4	18.641102	18.900859

3.0.2 It could be obeserved from the above table that both the model give almost similar results.