

Stochastic Gradient Descent From Scratch in Python



Author: Cristian Leo

Import Required Libraries

```
In [6]: # Basic Libraries
import numpy as np
import pandas as pd

# Load Data
from sklearn.datasets import load_diabetes

# Data Visualization
import matplotlib.pyplot as plt
import seaborn as sns

# Model Fine Tuning
import optuna

# Filter Warnings
import warnings
warnings.filterwarnings('ignore')
```

SGD Regressor Class

```
In [7]: class SGDRegressor:
def __init__(self, learning_rate=0.01, epochs=100, batch_size=1, reg=None
```

```
"""
```

```
Constructor for the SGDRegressor.
```

```
Parameters:
```

```
learning_rate (float): The step size used in each update.
```

```
epochs (int): Number of passes over the training dataset.
```

```
batch_size (int): Number of samples to be used in each batch.
```

```
reg (str): Type of regularization ('l1' or 'l2'); None if no regular
```

```
reg_param (float): Regularization parameter.
```

```
The weights and bias are initialized as None and will be set during
```

```
"""
```

```
self.learning_rate = learning_rate
```

```
self.epochs = epochs
```

```
self.batch_size = batch_size
```

```
self.reg = reg
```

```
self.reg_param = reg_param
```

```
self.weights = None
```

```
self.bias = None
```

```
def fit(self, X, y):
```

```
"""
```

```
Fits the SGDRegressor to the training data.
```

```
Parameters:
```

```
X (numpy.ndarray): Training data, shape (m_samples, n_features).
```

```
y (numpy.ndarray): Target values, shape (m_samples,).
```

```
This method initializes the weights and bias, and then updates them
```

```
"""
```

```
m, n = X.shape # m is number of samples, n is number of features
```

```
self.weights = np.zeros(n)
```

```
self.bias = 0
```

```
for _ in range(self.epochs):
```

```
    indices = np.random.permutation(m)
```

```
    X_shuffled = X[indices]
```

```
    y_shuffled = y[indices]
```

```
    for i in range(0, m, self.batch_size):
```

```
        X_batch = X_shuffled[i:i+self.batch_size]
```

```
        y_batch = y_shuffled[i:i+self.batch_size]
```

```
        gradient_w = -2 * np.dot(X_batch.T, (y_batch - np.dot(X_batch, self.weights) + self.bias))
```

```
        gradient_b = -2 * np.sum(y_batch - np.dot(X_batch, self.weights) + self.bias)
```

```
        if self.reg == 'l1':
```

```
            gradient_w += self.reg_param * np.sign(self.weights)
```

```
        elif self.reg == 'l2':
```

```
            gradient_w += self.reg_param * self.weights
```

```
        self.weights -= self.learning_rate * gradient_w
```

```
        self.bias -= self.learning_rate * gradient_b
```

```
def predict(self, X):
```

```
"""
```

```

    Predicts the target values using the linear model.

    Parameters:
    X (numpy.ndarray): Data for which to predict target values.

    Returns:
    numpy.ndarray: Predicted target values.
    """
    return np.dot(X, self.weights) + self.bias

def compute_loss(self, X, y):
    """
    Computes the loss of the model.

    Parameters:
    X (numpy.ndarray): The input data.
    y (numpy.ndarray): The true target values.

    Returns:
    float: The computed loss value.
    """
    return (np.mean((y - self.predict(X)) ** 2) + self._get_regularization_loss())

def _get_regularization_loss(self):
    """
    Computes the regularization loss based on the regularization type.

    Returns:
    float: The regularization loss.
    """
    if self.reg == 'l1':
        return self.reg_param * np.sum(np.abs(self.weights))
    elif self.reg == 'l2':
        return self.reg_param * np.sum(self.weights ** 2)
    else:
        return 0

def get_weights(self):
    """
    Returns the weights of the model.

    Returns:
    numpy.ndarray: The weights of the linear model.
    """
    return self.weights

```

Load Diabetes Data

```

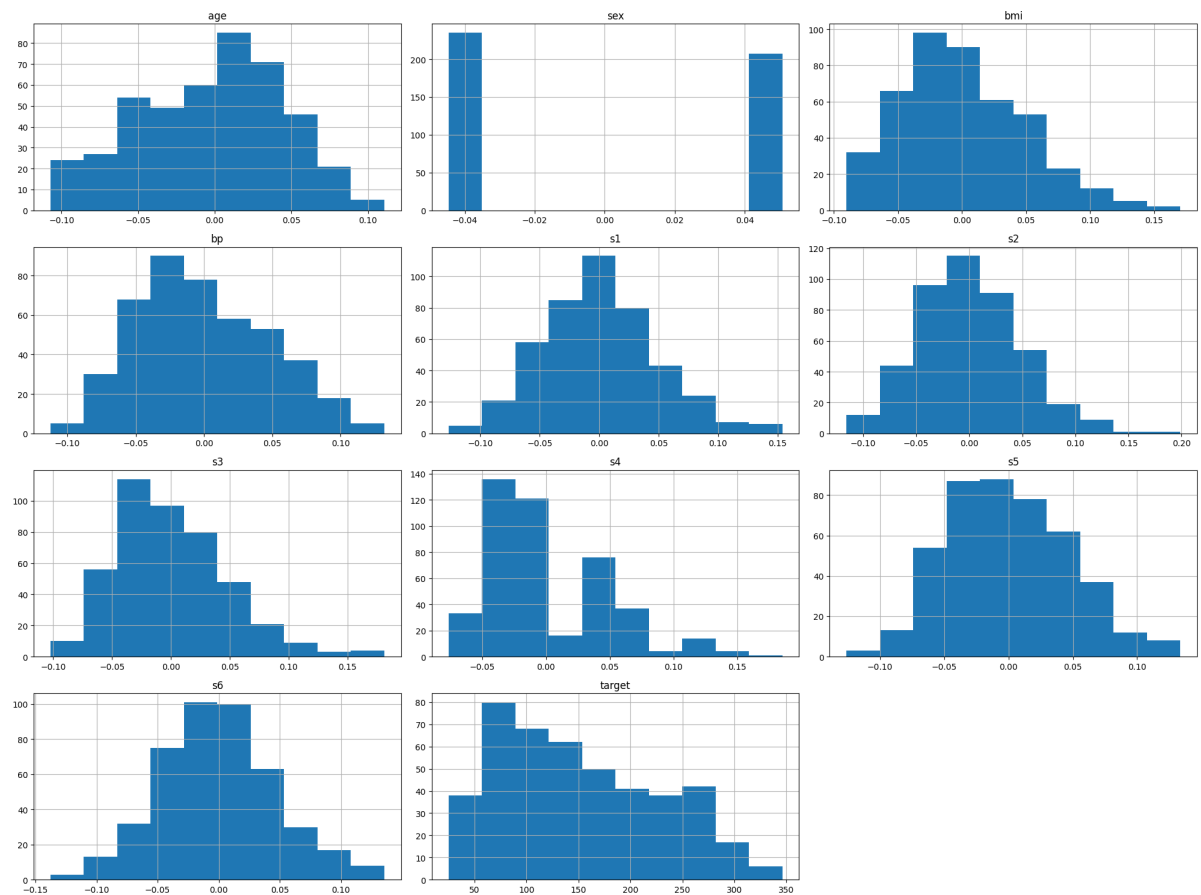
In [8]: # Load the diabetes dataset
diabetes = load_diabetes()
df = pd.DataFrame(data=diabetes.data, columns=diabetes.feature_names)
df['target'] = diabetes.target
df.head()

```

Out [8]:

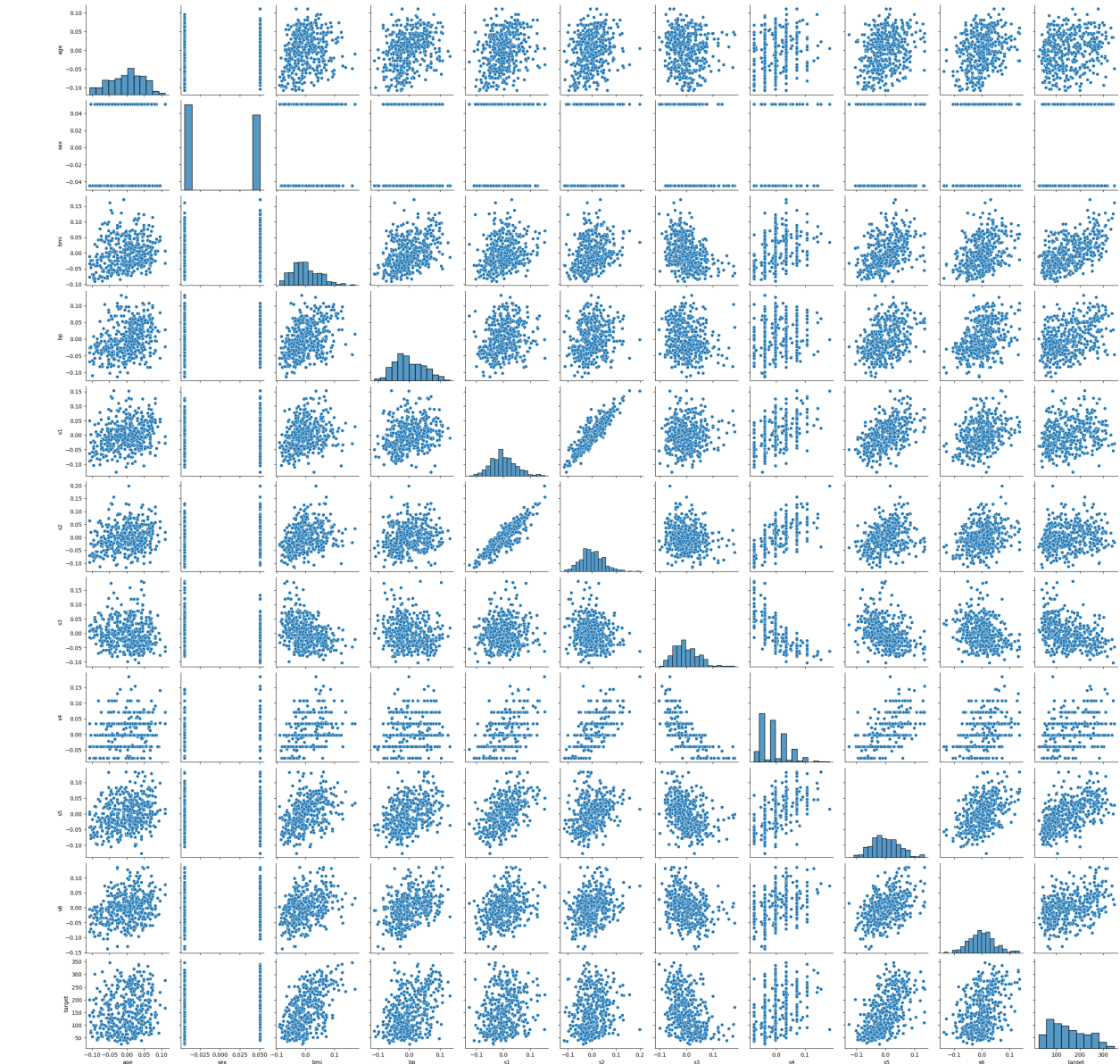
	age	sex	bmi	bp	s1	s2	s3	s4
0	0.038076	0.050680	0.061696	0.021872	-0.044223	-0.034821	-0.043401	-0.00259
1	-0.001882	-0.044642	-0.051474	-0.026328	-0.008449	-0.019163	0.074412	-0.03949
2	0.085299	0.050680	0.044451	-0.005670	-0.045599	-0.034194	-0.032356	-0.00259
3	-0.089063	-0.044642	-0.011595	-0.036656	0.012191	0.024991	-0.036038	0.03430
4	0.005383	-0.044642	-0.036385	0.021872	0.003935	0.015596	0.008142	-0.00259

```
In [9]: # Create histograms for each feature
df.hist(bins=10, figsize=(20, 15))
plt.tight_layout()
plt.show()
```



```
In [10]: # Pairplot of the features
sns.pairplot(df)
```

Out[10]: <seaborn.axisgrid.PairGrid at 0x2a4feb500>



Split Data

```
In [11]: # Get the input features (X) and target values (y)
X = diabetes.data
y = diabetes.target

# Split the dataset into training and test sets
def split_dataset(X, y, test_ratio=0.2):
    indices = np.random.permutation(len(X))
    test_size = int(len(X) * test_ratio)
    test_indices = indices[:test_size]
    train_indices = indices[test_size:]
    return X[train_indices], X[test_indices], y[train_indices], y[test_indices]

X_train, X_test, y_train, y_test = split_dataset(X, y)
X_train, X_val, y_train, y_val = split_dataset(X_train, y_train)
```

Fine-Tune Model with Optuna

```
In [12]: def objective(trial):
    learning_rate = trial.suggest_loguniform('learning_rate', 1e-3, 1e-1)
    epochs = trial.suggest_int('epochs', 30, 250)
    batch_size = trial.suggest_categorical('batch_size', [1, 10, 50, 100])
    reg_param = trial.suggest_loguniform('reg_param', 1e-5, 1e-1)
    reg = trial.suggest_categorical('reg', ['l1', 'l2'])

    regressor = SGDRegressor(learning_rate=learning_rate, epochs=epochs, bat
    regressor.fit(X_train, y_train)

    # Compute the validation loss
    val_loss = regressor.compute_loss(X_val, y_val)

    return val_loss

    optuna.logging.set_verbosity(optuna.logging.WARNING)
    study = optuna.create_study(direction='minimize')
    study.optimize(objective, n_trials=100)

    best_params = study.best_params
```

```
In [13]: for key, value in best_params.items():
    if key == 'reg':
        print(f'{key.capitalize()}: {value.capitalize()}')
    else:
        print(f'{key.capitalize()}: {value:.3f}')
```

```
Learning_rate: 0.050
Epochs: 143.000
Batch_size: 1.000
Reg_param: 0.000
Reg: L1
```

Predict Data

```
In [14]: best_regressor = SGDRegressor(learning_rate=best_params['learning_rate'], ep
best_regressor.fit(X_train, y_train)
predictions = best_regressor.predict(X_test)
loss = best_regressor.compute_loss(X_test, y_test)
print(f"Best model loss on test data: {loss:.2f}")
```

```
Best model loss on test data: 56.46
```