Adam Optimizer

February 3, 2024

1 Adam Optimizer from Scratch in Python

By Cristian Leo

Link Article: https://medium.com/towards-data-science/the-math-behind-adam-optimizer-c41407efe59b

1.1 Import Required Libraries

[1]:
```python
# 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
```

```python
# Model Fine Tuning
import optuna

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

```
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/site-
packages/tqdm/auto.py:21: TqdmWarning: IProgress not found. Please update
jupyter and ipywidgets. See
https://ipywidgets.readthedocs.io/en/stable/user_install.html
  from .autonotebook import tqdm as notebook_tqdm
```

1.2 Adam Optimizer Class

[2]:
```python
# Adam Optimizer (use the class from the previous response)
class AdamOptimizer:
    def __init__(self, learning_rate=0.001, beta1=0.9, beta2=0.999,␣
 ↪epsilon=1e-8):
        """
        Constructor for the AdamOptimizer class.

        Parameters
        ----------
        learning_rate : float
            Learning rate for the optimizer.
        beta1 : float
            Exponential decay rate for the first moment estimates.
        beta2 : float
            Exponential decay rate for the second moment estimates.
        epsilon : float
            Small value to prevent division by zero.

        Returns
        -------
        None.
        """
        self.learning_rate = learning_rate
        self.beta1 = beta1
        self.beta2 = beta2
        self.epsilon = epsilon
        self.m = None
        self.v = None
        self.t = 0

    def initialize_moments(self, params):
```

```
        """
        Initializes the first and second moment estimates.

        Parameters
        ----------
        params : dict
            Dictionary containing the model parameters.

        Returns
        -------
        None.
        """
        self.m = {k: np.zeros_like(v) for k, v in params.items()}
        self.v = {k: np.zeros_like(v) for k, v in params.items()}

    def update_params(self, params, grads):
        """
        Updates the model parameters using the Adam optimizer.

        Parameters
        ----------
        params : dict
            Dictionary containing the model parameters.
        grads : dict
            Dictionary containing the gradients for each parameter.

        Returns
        -------
        updated_params : dict
            Dictionary containing the updated model parameters.
        """
        if self.m is None or self.v is None:
            self.initialize_moments(params)

        self.t += 1
        updated_params = {}

        for key in params.keys():
            self.m[key] = self.beta1 * self.m[key] + (1 - self.beta1) *␣
↪grads[key]
            self.v[key] = self.beta2 * self.v[key] + (1 - self.beta2) * np.
↪square(grads[key])

            m_corrected = self.m[key] / (1 - self.beta1 ** self.t)
            v_corrected = self.v[key] / (1 - self.beta2 ** self.t)
```

```
            updated_params[key] = params[key] - self.learning_rate *␣
↪m_corrected / (np.sqrt(v_corrected) + self.epsilon)

        return updated_params
```

1.3 Linear Regression Class

[3]:
```
# Linear Regression Model
class LinearRegression:
    def __init__(self, n_features):
        """
        Constructor for the LinearRegression class.

        Parameters
        ----------
        n_features : int
            Number of features in the input data.

        Returns
        -------
        None.
        """
        self.weights = np.random.randn(n_features)
        self.bias = np.random.randn()

    def predict(self, X):
        """
        Predicts the target variable given the input data.

        Parameters
        ----------
        X : numpy array
            Input data.

        Returns
        -------
        numpy array
            Predictions.
        """
        return np.dot(X, self.weights) + self.bias
```

1.4 Model Trainer Class

[36]:
```
class ModelTrainer:
    def __init__(self, model, optimizer, n_epochs):
        """
```

```
        Constructor for the ModelTrainer class.

        Parameters
        ----------
        model : object
            Model to be trained.
        optimizer : object
            Optimizer to be used for training.
        n_epochs : int
            Number of training epochs.

        Returns
        -------
        None.
        """
        self.model = model
        self.optimizer = optimizer
        self.n_epochs = n_epochs

    def compute_gradients(self, X, y):
        """
        Computes the gradients of the mean squared error loss function
        with respect to the model parameters.

        Parameters
        ----------
        X : numpy array
            Input data.
        y : numpy array
            Target variable.

        Returns
        -------
        dict
            Dictionary containing the gradients for each parameter.
        """
        predictions = self.model.predict(X)
        errors = predictions - y
        dW = 2 * np.dot(X.T, errors) / len(y)
        db = 2 * np.mean(errors)
        return {'weights': dW, 'bias': db}

    def train(self, X, y, verbose=False):
        """
        Runs the training loop, updating the model parameters and optionally␣
↪printing the loss.
```

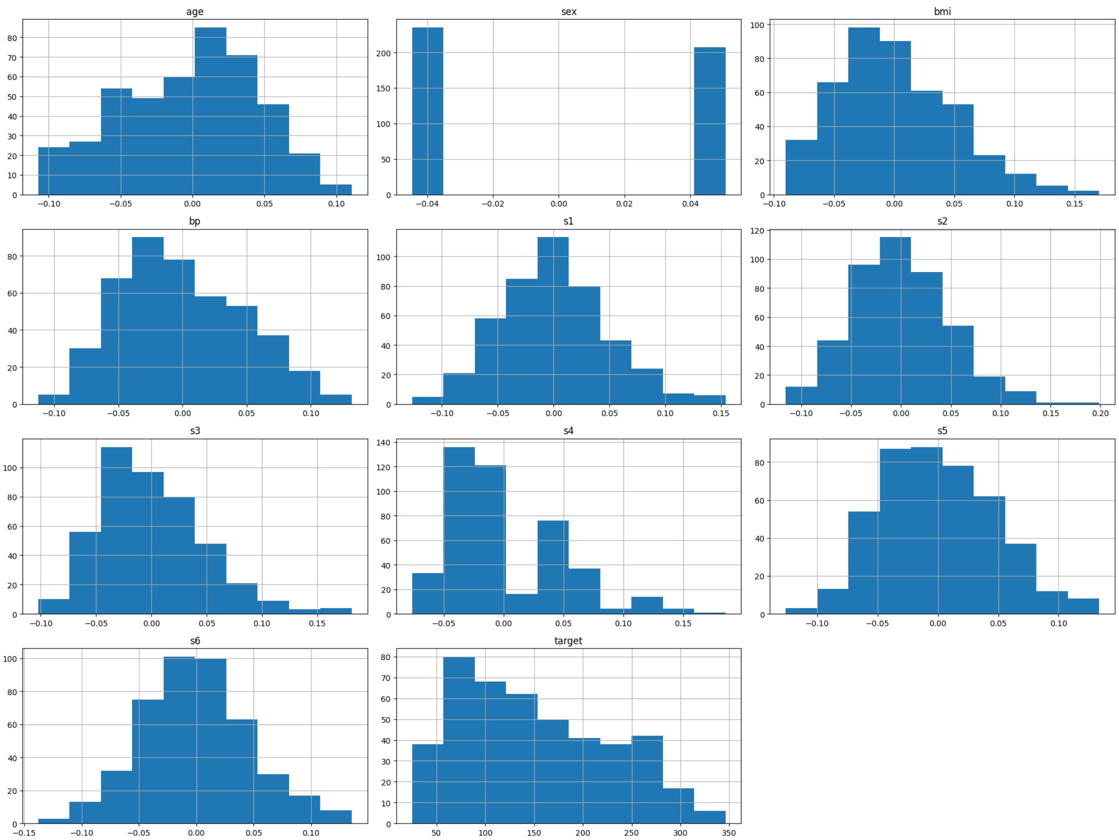
```
        Parameters
        ----------
        X : numpy array
            Input data.
        y : numpy array
            Target variable.

        Returns
        -------
        None.
        """
        for epoch in range(self.n_epochs):
            grads = self.compute_gradients(X, y)
            params = {'weights': self.model.weights, 'bias': self.model.bias}
            updated_params = self.optimizer.update_params(params, grads)

            self.model.weights = updated_params['weights']
            self.model.bias = updated_params['bias']

            # Optionally, print loss here to observe training
            loss = np.mean((self.model.predict(X) - y) ** 2)
            if epoch % 1000 == 0 and verbose:
                print(f"Epoch {epoch}, Loss: {loss}")
```

1.5 Load Diabetes Data

[16]:
```
# Load the diabetes dataset
diabetes = load_diabetes()
df = pd.DataFrame(data=diabetes.data, columns=diabetes.feature_names)
df['target'] = diabetes.target
df.head()
```

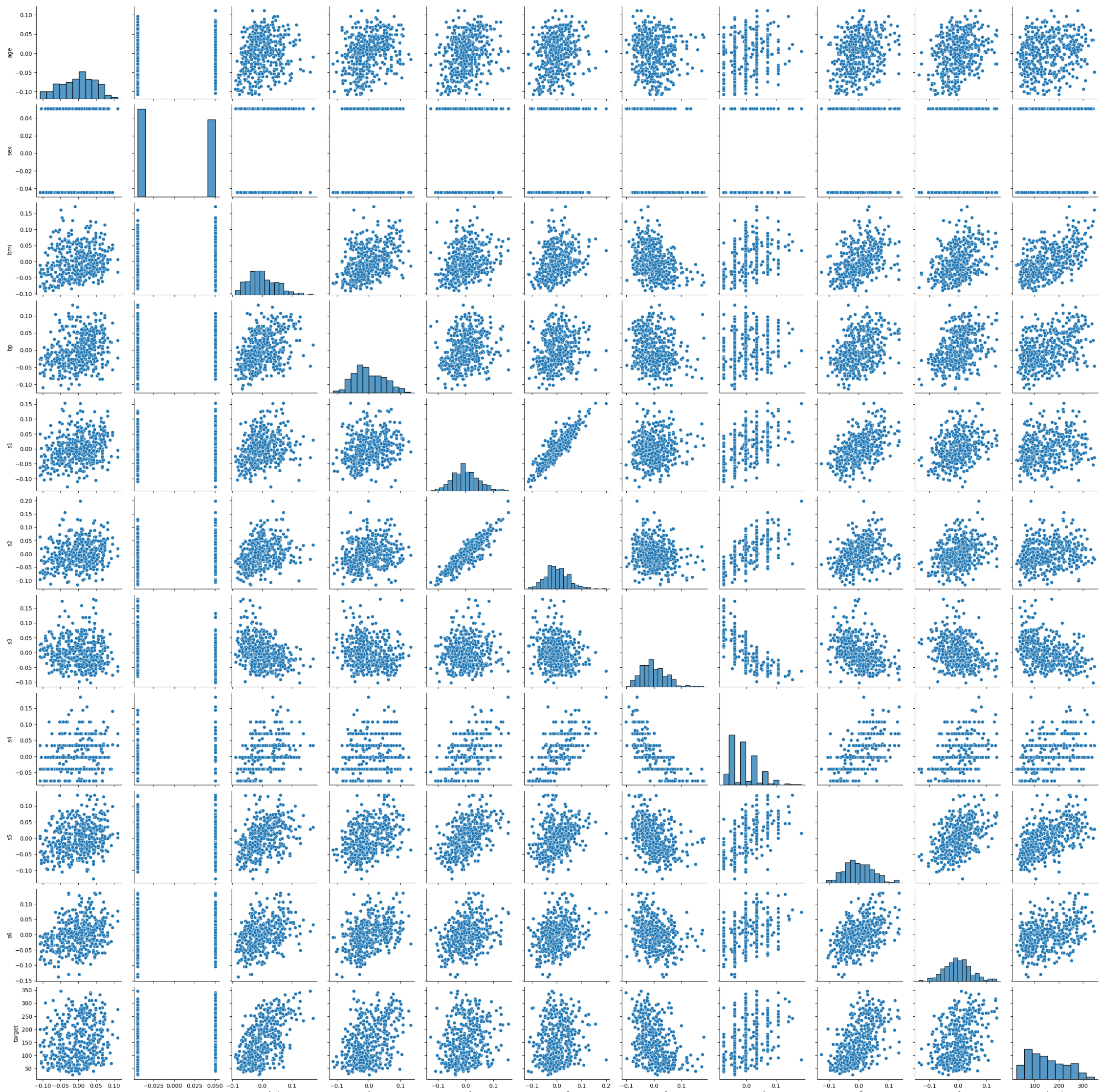
[16]:
```
        age       sex       bmi        bp        s1        s2        s3  \
0  0.038076  0.050680  0.061696  0.021872 -0.044223 -0.034821 -0.043401
1 -0.001882 -0.044642 -0.051474 -0.026328 -0.008449 -0.019163  0.074412
2  0.085299  0.050680  0.044451 -0.005670 -0.045599 -0.034194 -0.032356
3 -0.089063 -0.044642 -0.011595 -0.036656  0.012191  0.024991 -0.036038
4  0.005383 -0.044642 -0.036385  0.021872  0.003935  0.015596  0.008142

         s4        s5        s6  target
0 -0.002592  0.019907 -0.017646   151.0
1 -0.039493 -0.068332 -0.092204    75.0
2 -0.002592  0.002861 -0.025930   141.0
3  0.034309  0.022688 -0.009362   206.0
4 -0.002592 -0.031988 -0.046641   135.0
```

[17]:
```python
# Create histograms for each feature
df.hist(bins=10, figsize=(20, 15))
plt.tight_layout()
plt.show()
```



[18]:
```python
# Pairplot of the features
sns.pairplot(df)
```

[18]: `<seaborn.axisgrid.PairGrid at 0x29ed37500>`



1.6 Split Data

[19]:
```python
# 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)
```

1.7 Fine Tune Model with Optuna

[20]:
```
y_train.shape
```

[20]: (284,)

[37]:
```
def objective(trial):
    n_features = X_train.shape[1]

    learning_rate = trial.suggest_loguniform('learning_rate', 1e-5, 1e-1)
    beta1 = trial.suggest_uniform('beta1', 0.9, 0.999)
    beta2 = trial.suggest_uniform('beta2', 0.99, 0.9999)
    epsilon = trial.suggest_loguniform('epsilon', 1e-10, 1e-5)

    n_epochs = trial.suggest_int('epochs', 1000, 100000)

    # Define the model
    model = LinearRegression(n_features)
    optimizer = AdamOptimizer(learning_rate=learning_rate, beta1=beta1,␣
 ↪beta2=beta2, epsilon=epsilon)
    trainer = ModelTrainer(model, optimizer, n_epochs=n_epochs)

    # Train the model
    trainer.train(X_train, y_train, verbose=False)

    # Compute the validation loss
    val_loss = np.mean((model.predict(X_val) - y_val) ** 2)

    return val_loss

# Create the study object
optuna.logging.set_verbosity(optuna.logging.WARNING)
study = optuna.create_study(direction='minimize', sampler=optuna.samplers.
 ↪TPESampler(seed=42))

# Optimize the study, use more trials to obtain better results, use less trials␣
 ↪to be more cost-efficient
study.optimize(objective, n_trials=10)
```

[38]:
```
# Print optimization results
print("----------------------------------------")
print('Number of finished trials:', len(study.trials))
```

```python
print('Best trial:')
for key, value in study.best_trial.params.items():
    if key == 'epochs' or key == 'epsilon':
        print(f'    {key}: {value}')
    else:
        print(f'    {key}: {value:.3f}')
```

```
---------------------------------------
Number of finished trials: 10
Best trial:
    learning_rate: 0.017
    beta1: 0.930
    beta2: 0.991
    epsilon: 2.637333993381524e-07
    epochs: 44575
```

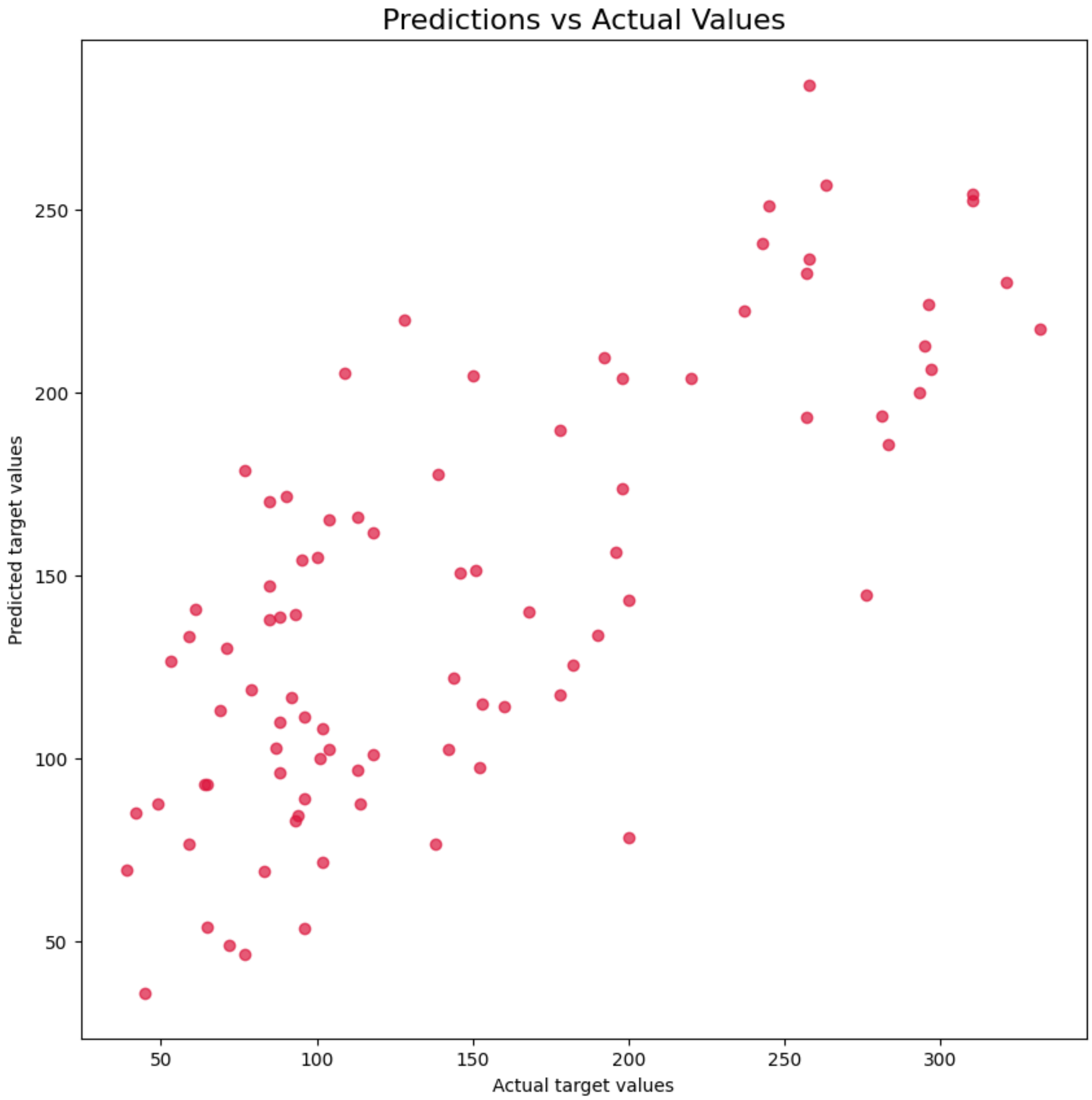
[40]:

```python
# Get the best model
n_features = X_train.shape[1]
best_model = LinearRegression(n_features)
optimizer = AdamOptimizer(learning_rate=study.best_params['learning_rate'],
                          beta1=study.best_params['beta1'],
                          beta2=study.best_params['beta2'],
                          epsilon=study.best_params['epsilon'])

# Train the model
trainer = ModelTrainer(best_model, optimizer, n_epochs=study.
 ↪best_params['epochs'])
trainer.train(X_train, y_train)

# Compute the test loss
test_loss = np.mean((best_model.predict(X_test) - y_test) ** 2)**0.5
print(f'Test loss: {test_loss:.2f}')
```

```
Test loss: 53.55
```

[31]:

```python
# Plot the predictions vs the actual values
plt.figure(figsize=(10, 10))
plt.scatter(y_test, best_model.predict(X_test), c='crimson', alpha=0.7)
plt.title('Predictions vs Actual Values', fontsize=16)
plt.xlabel('Actual target values')
plt.ylabel('Predicted target values')
plt.show()
```


Predictions vs Actual Values
Predicted target values
Actual target values
50
100
150
200
250
300