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DLL EXPERIMENT NO : 04

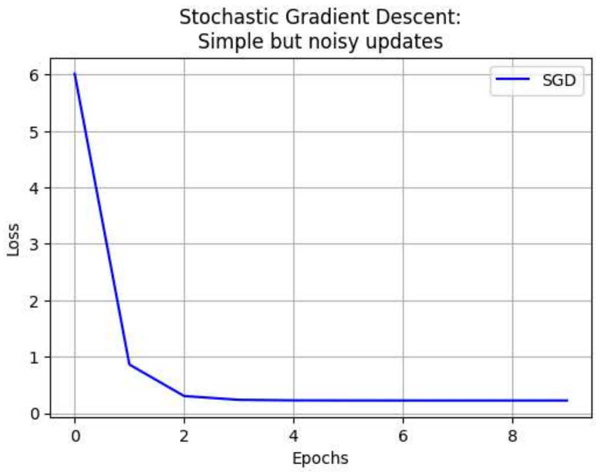
AIM : Apply any of the following learning algorithms to learn the parameters of the supervised single layer feedforward neural network:

a. Stochastic Gradient Descent, b. Mini Batch Gradient Descent, c. Momentum GD, d. Nesterov GD, e. Adagrad GD, f. Adam Learning GD

a. Stochastic Gradient Descent (SGD)

Explanation: Updates are made after each training example, giving very frequent updates. May be noisy but fast to converge in some cases.

```
import numpy as np
import matplotlib.pyplot as plt

# Sample synthetic data
#np.random.seed(0) sets the random seed for reproducibility.
#X is a matrix of shape (100 samples, 3 features), generated from a normal distribution.
#true_W is the actual weights we use to generate targets.
#y is the target values generated by multiplying X with true_W plus some noise (0.5 * np.random.randn(...)) to simulate realistic imperfect data.
#When you set a seed, you're telling the random number generator where to start.
#This means every time you run your code with the same seed, it will produce the exact same sequence of random numbers.
np.random.seed(0)


true_W = np.array([[2.0], [-3.5], [1.0]])
y = X @ true_W + 0.5 * np.random.randn(100, 1)

# Initialize parameters
W = np.random.randn(3, 1)
b = 0.0
lr = 0.01

loss_sgd = [] #Loss Tracking Initialization

# Loop over each data point for 10 epochs
#Outer loop runs 10 epochs (passes over the entire dataset).
#Inner loop iterates over each individual training example (X.shape[0] == 100).
#xi and yi extract a single data point (row) and its corresponding label.
#This per-sample update is what defines stochastic gradient descent (SGD).

for epoch in range(10):
    epoch_loss = 0
    for i in range(X.shape[0]):
        xi = X[i:i+1]
        yi = y[i:i+1]

        # Forward pass
        y_pred = xi @ W + b

        # Compute loss for monitoring #Calculate mean squared error (MSE) for the single sample prediction.
        loss = np.mean((y_pred - yi) ** 2)
        epoch_loss += loss

        #Backward Pass (Gradient Calculation)
        # Compute gradients
        #Calculate the error term: predicted minus true.
#Compute gradient of weights dW using the chain rule.
#xi.T is transpose of input (3x1).
#error is scalar (1x1).
#So dW is (3x1) vector — gradient for each weight.
#Compute gradient for bias db (scalar).

        error = y_pred - yi
        dW = xi.T @ error
        db = np.sum(error)

        # Parameter update
        W -= lr * dW
        b -= lr * db

    # Average loss per epoch
    loss_sgd.append(epoch_loss / X.shape[0])

# Plot loss after training
plt.figure(figsize=(6,4))
plt.plot(loss_sgd, label='SGD', color='blue')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.title('Stochastic Gradient Descent:\nSimple but noisy updates')
plt.legend()
plt.grid(True)
plt.show()
```



f. Adam Optimizer

Explanation: Combines momentum and adaptive learning rate. One of the most popular optimizers in deep learning.

```
import numpy as np
import matplotlib.pyplot as plt

# Sample synthetic data
np.random.seed(0)
X = np.random.randn(100, 3)
true_W = np.array([[2.0], [-3.5], [1.0]])
y = X @ true_W + 0.5 * np.random.randn(100, 1)

# Initialize parameters
W = np.random.randn(3, 1)
b = 0.0
lr = 0.01

#beta1 controls the decay rate for the first moment estimate (momentum-like term).
#beta2 controls the decay rate for the second moment estimate (variance or RMSProp-like term).
#eps is a small number added to denominators to avoid division by zero.
beta1 = 0.9
beta2 = 0.999
eps = 1e-8

#m_W and m_b store the first moments (exponentially weighted averages of gradients).
#v_W and v_b store the second moments (exponentially weighted averages of squared gradients).
#Initialized to zero arrays with the same shapes as parameters.

m_W = np.zeros_like(W)
v_W = np.zeros_like(W)
m_b = np.zeros_like(b)
v_b = np.zeros_like(b)

loss_adam = []

for epoch in range(1, 11):  # Epoch 1 to 10
    y_pred = X @ W + b
    error = y_pred - y

    # Compute loss and store
    loss = np.mean(error ** 2)
    loss_adam.append(loss)

    # Compute gradients
    dW = X.T @ error / X.shape[0]
    db = np.sum(error) / X.shape[0]

    # Update biased first moment estimate
    m_W = beta1 * m_W + (1 - beta1) * dW
    m_b = beta1 * m_b + (1 - beta1) * db

    # Update biased second moment estimate
    v_W = beta2 * v_W + (1 - beta2) * (dW ** 2)
    v_b = beta2 * v_b + (1 - beta2) * (db ** 2)

    # Compute bias-corrected first moment estimate
    m_W_hat = m_W / (1 - beta1 ** epoch)
    m_b_hat = m_b / (1 - beta1 ** epoch)

    # Compute bias-corrected second moment estimate
    v_W_hat = v_W / (1 - beta2 ** epoch)
    v_b_hat = v_b / (1 - beta2 ** epoch)

    # Update parameters
    W -= lr * m_W_hat / (np.sqrt(v_W_hat) + eps)
    b -= lr * m_b_hat / (np.sqrt(v_b_hat) + eps)

# Plot loss curve
```

```
plt.figure(figsize=(6,4))
plt.plot(loss_adam, label='Adam GD', color='brown')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.title('Adam Optimizer:\nAdaptive momentum with bias correction')
plt.legend()
plt.grid(True)
plt.show()

#This code implements the Adam optimizer for linear regression.
#Adam combines the benefits of momentum and adaptive learning rates.
#The random seed guarantees the synthetic data and initialization remain the same on every run.
#The loss plot helps verify that the optimizer is effectively minimizing the error.
```