

Experiment no 3

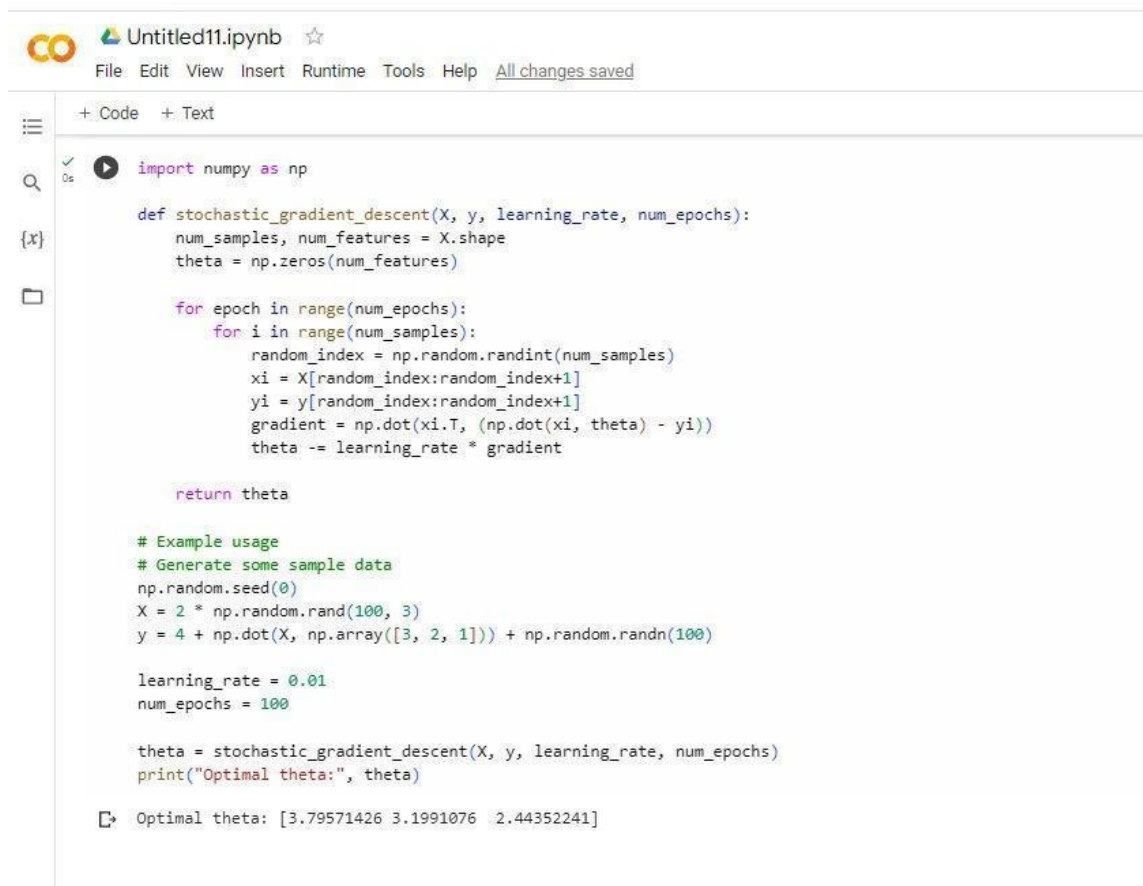
Implementation of stochastic gradient descent

```
import numpy as np

def stochastic_gradient_descent(X, y, learning_rate, num_epochs):
    num_samples, num_features = X.shape
    theta = np.zeros(num_features)
    for epoch in range(num_epochs):
        for i in range(num_samples):
            random_index = np.random.randint(num_samples)
            xi = X[random_index:random_index+1]
            yi = y[random_index:random_index+1]
            gradient = np.dot(xi.T, (np.dot(xi, theta) - yi))
            theta -= learning_rate * gradient
    return theta

# Example usage
# Generate some sample data
```

```
np.random.seed(0)
X = 2 * np.random.rand(100, 3)
y = 4 + np.dot(X, np.array([3, 2, 1])) + np.random.randn(100)
learning_rate = 0.01
num_epochs = 100
theta = stochastic_gradient_descent(X, y, learning_rate, num_epochs)
print("Optimal theta:", theta)
```



The image shows a Jupyter Notebook interface with a file named 'Untitled11.ipynb'. The notebook contains a Python script that implements a stochastic gradient descent algorithm. The script defines a function `stochastic_gradient_descent` that takes `X`, `y`, `learning_rate`, and `num_epochs` as arguments. Inside the function, it initializes `num_samples` and `num_features` from `X`, and sets `theta` to a zero vector. It then enters a loop over `num_epochs`, and for each epoch, it loops over `num_samples`. In each iteration, it selects a random sample `xi` from `X` and `yi` from `y`, calculates the gradient, and updates `theta` by subtracting the product of the learning rate and the gradient. After the loops, it returns `theta`. Below the function definition, there is an example usage section that generates sample data, sets the learning rate to 0.01 and the number of epochs to 100, calls the `stochastic_gradient_descent` function, and prints the optimal theta. The output of the notebook shows the optimal theta as `[3.79571426 3.1991076 2.44352241]`.

```
import numpy as np

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    num_samples, num_features = X.shape
    theta = np.zeros(num_features)

    for epoch in range(num_epochs):
        for i in range(num_samples):
            random_index = np.random.randint(num_samples)
            xi = X[random_index:random_index+1]
            yi = y[random_index:random_index+1]
            gradient = np.dot(xi.T, (np.dot(xi, theta) - yi))
            theta -= learning_rate * gradient

    return theta

# Example usage
# Generate some sample data
np.random.seed(0)
X = 2 * np.random.rand(100, 3)
y = 4 + np.dot(X, np.array([3, 2, 1])) + np.random.randn(100)

learning_rate = 0.01
num_epochs = 100

theta = stochastic_gradient_descent(X, y, learning_rate, num_epochs)
print("Optimal theta:", theta)
```

Optimal theta: [3.79571426 3.1991076 2.44352241]

Implementation of mini batch gradient descent

```
import numpy as np

# Define the function to be minimized and its
gradient def f(x):
    return x**2

def df(x):
    return 2*x

# Define the mini-batch gradient descent function
def minibatch_gradient_descent(x_init, learning_rate, batch_size, num_iterations):
    x = x_init
    for i in range(num_iterations):
        # Generate random mini-batch samples
        indices = np.random.choice(len(x), size=batch_size)
        batch = x[indices]
        # Compute the gradient of the mini-batch loss
        gradient = np.mean(df(batch))
        # Update the parameter using the learning rate and mini-batch gradient
        x -= learning_rate * gradient
```

```
return x

# Test the mini-batch gradient descent function

x_init = np.array([1.0, 2.0, 3.0, 4.0])

learning_rate = 0.1

batch_size = 2

num_iterations = 100

result = minibatch_gradient_descent(x_init, learning_rate, batch_size,
num_iterations)

print("Result:", result)
```

```

import numpy as np

# Define the function to be minimized and its gradient
def f(x):
    return x**2

def df(x):
    return 2*x

# Define the mini-batch gradient descent function
def minibatch_gradient_descent(x_init, learning_rate, batch_size, num_iterations):
    x = x_init
    for i in range(num_iterations):
        # Generate random mini-batch samples
        indices = np.random.choice(len(x), size=batch_size)
        batch = x[indices]

        # Compute the gradient of the mini-batch loss
        gradient = np.mean(df(batch))

        # Update the parameter using the learning rate and mini-batch gradient
        x -= learning_rate * gradient

    return x

# Test the mini-batch gradient descent function
x_init = np.array([1.0, 2.0, 3.0, 4.0])
learning_rate = 0.1
batch_size = 2
num_iterations = 100

result = minibatch_gradient_descent(x_init, learning_rate, batch_size, num_iterations)
print("Result:", result)

```

Result: [-1.4231927 -0.4231927 0.5768073 1.5768073]