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CS20BTECH11063

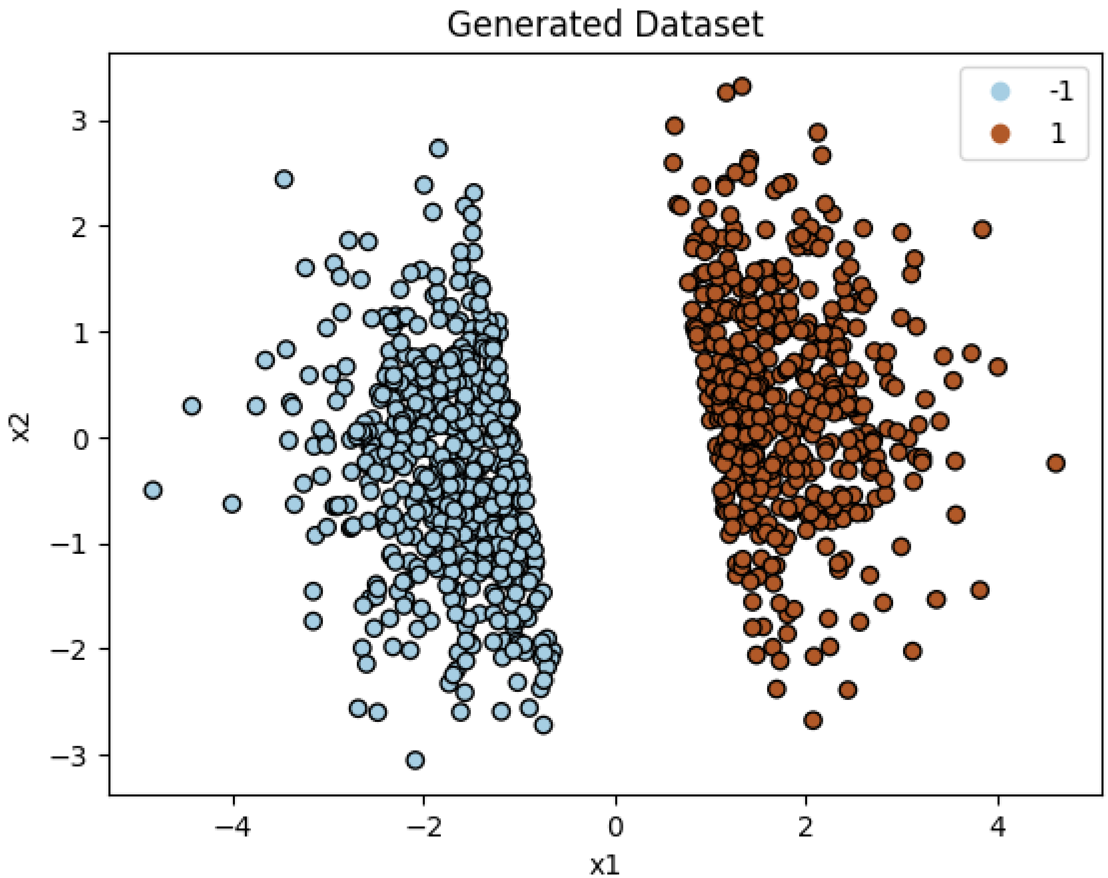
Deep Learning Assignment 1

In [ ]:
```
import torch
import numpy as np
import matplotlib.pyplot as plt
import math
import torch.functional as F
import torch.nn as nn
```

Q1

In [ ]:
```
# Create a Linearly separable 2D dataset

# Use a different function to generate the dataset
def create_dataset(n=100, gamma=0.1):
    x = torch.randn(n, 2)
    y = torch.zeros(n)

    # for i in range(n):
    #     y[i] = 1 if x[i, 0] + gamma * x[i, 1] > 0 else -1
    # return x, y

    # Random initialize the weights and bias
    w = torch.randn(2)
    b = torch.randn(1)

    # Create the Dataset
    y = torch.sign(torch.matmul(x, w) + b)
    y[np.random.rand(n) < gamma] *= -1
    return x, y

def create_dataset_2(n=100, gamma=1):
```

```
    x = torch.randn(n, 2)
    y = torch.zeros(n)

    # Random initialize the weights and bias
    w = np.random.rand(2)

    # Create the Dataset
    y = torch.sign(torch.matmul(x, torch.Tensor(w)))

    # Angle of the line
    theta = np.arctan(w[1]/w[0])

    # apply the separability factor and point shifter to separate data based on separability factor and angle of the line
    point_shifter = np.array([np.cos(theta), np.sin(theta)])

    x = x.numpy()
    x[y==1] = x[y==1] + (gamma-1) * point_shifter
    x[y==-1] = x[y==-1] - (gamma-1) * point_shifter

    return torch.Tensor(x), y

# Plot the scatter plot with legend
x, y = create_dataset_2(1000, 2)

scatter = plt.scatter(x[:, 0], x[:, 1], c=y, cmap=plt.cm.Paired, edgecolors='k')
xmin, xmax, ymin, ymax = plt.axis()
plt.title("Generated Dataset")
plt.xlabel("x1")
plt.ylabel("x2")
plt.legend(handles=scatter.legend_elements()[0], labels=["-1", "1"])
plt.show()


# print frequency percentage of labels
print("Percentage of -1 labels: ", (y == -1).sum().item() / len(y))
print("Percentage of 1 labels: ", (y == 1).sum().item() / len(y))
```




```
Percentage of -1 labels:  0.517
Percentage of 1 labels:  0.483
```

In [ ]:

```python
# split dataset into train and test
def split_dataset(x, y, train_ratio=0.8):
    n = len(x)
    train_size = int(train_ratio * n)
    x_train = x[:train_size]
    y_train = y[:train_size]
    x_test = x[train_size:]
    y_test = y[train_size:]
    return x_train, y_train, x_test, y_test

# x_train, y_train, x_test, y_test = split_dataset(x, y, 0.8)
```

In [ ]:

```python
# Append 1 to x for bias
x = torch.cat((x, torch.ones(x.shape[0], 1)), dim=1)
```

```python
print("Shape of x: ", x.shape)
print("Shape of y: ", y.shape)
# print(x)
```

```
Shape of x:  torch.Size([1000, 3])
Shape of y:  torch.Size([1000])
```

In [ ]:

```python
# Perceptron Training Algorithm
def perceptron_train(x, y, max_epochs=100):
    w = torch.zeros(3)
    k = 0
    for epoch in range(max_epochs):
        nb_changes = 0
        for i in range(x.size(0)):
            if x[i].dot(w) * y[i] <= 0:
                w = w + y[i] * x[i]
                nb_changes = nb_changes + 1
        if nb_changes == 0:
            # print('Stopping at Epoch: ', epoch)
            break
        k = k + 1
    # print('Number of changes: ', nb_changes)

    # return the weights and number of epochs
    return w, k
```

In [ ]:

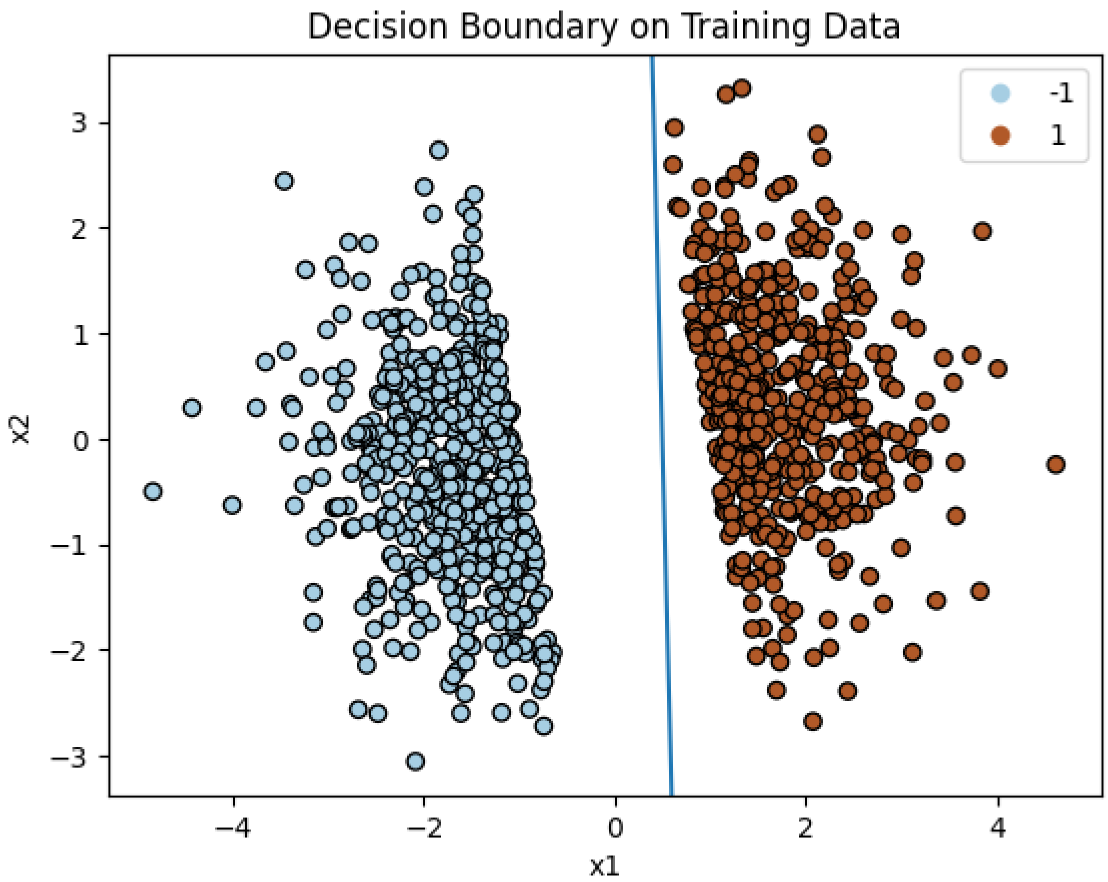
```python
w, max_epochs_run = perceptron_train(x, y, 100)
print("W = ", w, " Max Epochs Run = ", max_epochs_run)
```

```
W =  tensor([ 2.0111,  0.0590, -1.0000])  Max Epochs Run =  1
```

In [ ]:

```python
# plot the decision boundary on data
x1 = np.linspace(-5, 5, 100)
x2 = -(w[0] * x1 + w[2]) / w[1]
plt.plot(x1, x2)

scatter = plt.scatter(x[:, 0], x[:, 1], c=y, cmap=plt.cm.Paired, edgecolors='k')
plt.ylim(ymin, ymax)
plt.xlim(xmin, xmax)
plt.xlabel("x1")
plt.ylabel("x2")
plt.title("Decision Boundary on Training Data")
plt.legend(handles=scatter.legend_elements()[0], labels=["-1", "1"])
plt.show()
```

```python
# print accuracy on test data
y_pred = torch.sign(x @ w)
print("Accuracy = ", (torch.sum(y_pred == y) / y.shape[0]).item() * 100, "%")
```



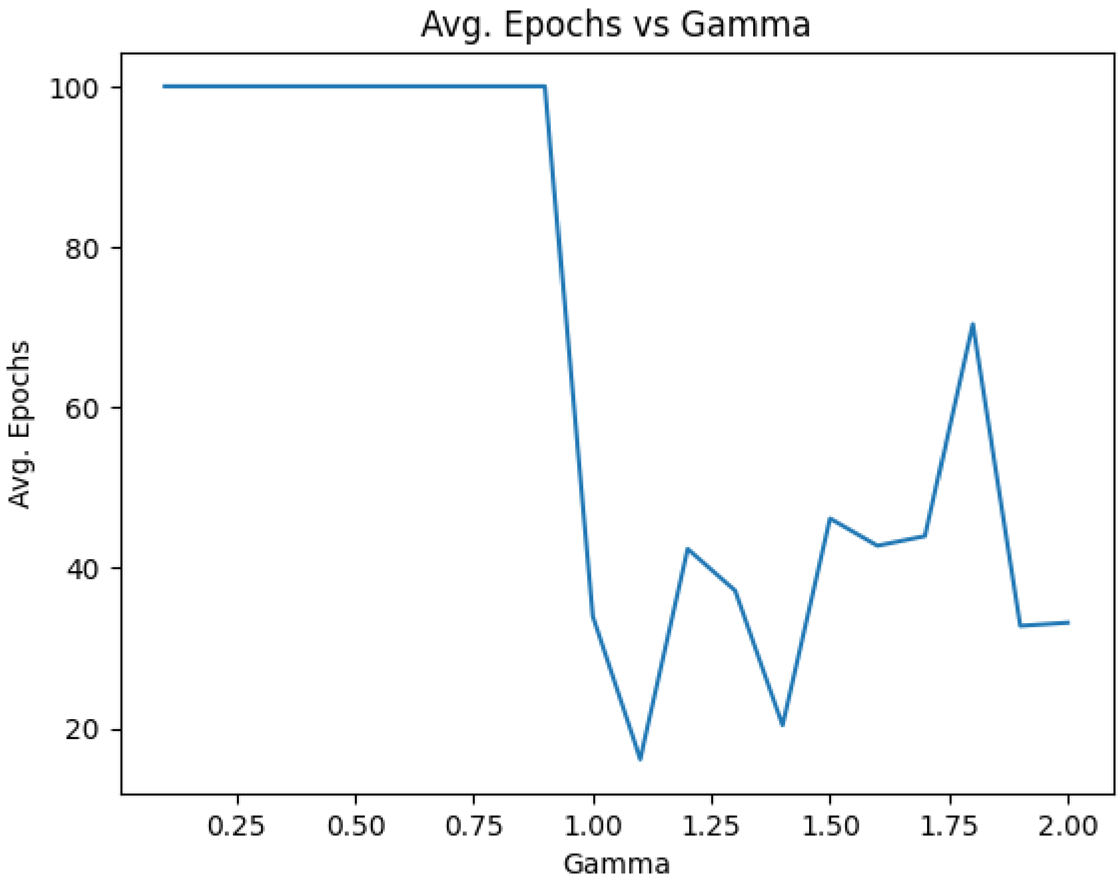

```
Accuracy =  100.0 %
```

In [ ]:

```python
# Running the perceptron training algorithm for different values of gamma for multiple trials
num_trials = 5
gamma_val = []
k_val = []
for gamma in np.linspace(0.1, 2, 20):
    acc = 0
    k_avg = 0
    for i in range(num_trials):
        x, y = create_dataset(1000, gamma)
```

```
        # split dataset into train and test
        x_train, y_train, x_test, y_test = split_dataset(x, y, 0.8)
        # x = x_train
        # y = y_train

        x_train = torch.cat((x_train, torch.ones(x_train.shape[0], 1)), dim=1)
        w, k = perceptron_train(x_train, y_train, 100)
        k_avg = k_avg + k

        x_test = torch.cat((x_test, torch.ones(x_test.shape[0], 1)), dim=1)
        y_pred = torch.sign(x_test @ w)
        acc = acc + torch.sum(y_pred == y_test) / y_test.shape[0]

        # print('----------------------------------------------')
    k_avg = k_avg / num_trials
    gamma_val.append(gamma)
    k_val.append(k_avg)
    print('Gamma: %f, Accuracy: %f, Avg. Epochs: %f' % (gamma, acc / num_trials, k_avg))

    # print('----------------------------------------------')

plt.plot(gamma_val, k_val)
plt.xlabel('Gamma')
plt.ylabel('Avg. Epochs')
plt.title('Avg. Epochs vs Gamma')
plt.show()
```

```
Gamma: 0.100000, Accuracy: 0.744000, Avg. Epochs: 100.000000
Gamma: 0.200000, Accuracy: 0.695000, Avg. Epochs: 100.000000
Gamma: 0.300000, Accuracy: 0.555000, Avg. Epochs: 100.000000
Gamma: 0.400000, Accuracy: 0.488000, Avg. Epochs: 100.000000
Gamma: 0.500000, Accuracy: 0.489000, Avg. Epochs: 100.000000
Gamma: 0.600000, Accuracy: 0.574000, Avg. Epochs: 100.000000
Gamma: 0.700000, Accuracy: 0.559000, Avg. Epochs: 100.000000
Gamma: 0.800000, Accuracy: 0.652000, Avg. Epochs: 100.000000
Gamma: 0.900000, Accuracy: 0.754000, Avg. Epochs: 100.000000
Gamma: 1.000000, Accuracy: 0.998000, Avg. Epochs: 34.000000
Gamma: 1.100000, Accuracy: 0.998000, Avg. Epochs: 16.200000
Gamma: 1.200000, Accuracy: 0.996000, Avg. Epochs: 42.400000
Gamma: 1.300000, Accuracy: 0.995000, Avg. Epochs: 37.200000
Gamma: 1.400000, Accuracy: 0.999000, Avg. Epochs: 20.400000
Gamma: 1.500000, Accuracy: 0.999000, Avg. Epochs: 46.200000
Gamma: 1.600000, Accuracy: 0.997000, Avg. Epochs: 42.800000
Gamma: 1.700000, Accuracy: 0.996000, Avg. Epochs: 44.000000
Gamma: 1.800000, Accuracy: 1.000000, Avg. Epochs: 70.400000
Gamma: 1.900000, Accuracy: 0.999000, Avg. Epochs: 32.800000
Gamma: 2.000000, Accuracy: 0.999000, Avg. Epochs: 33.200000
```



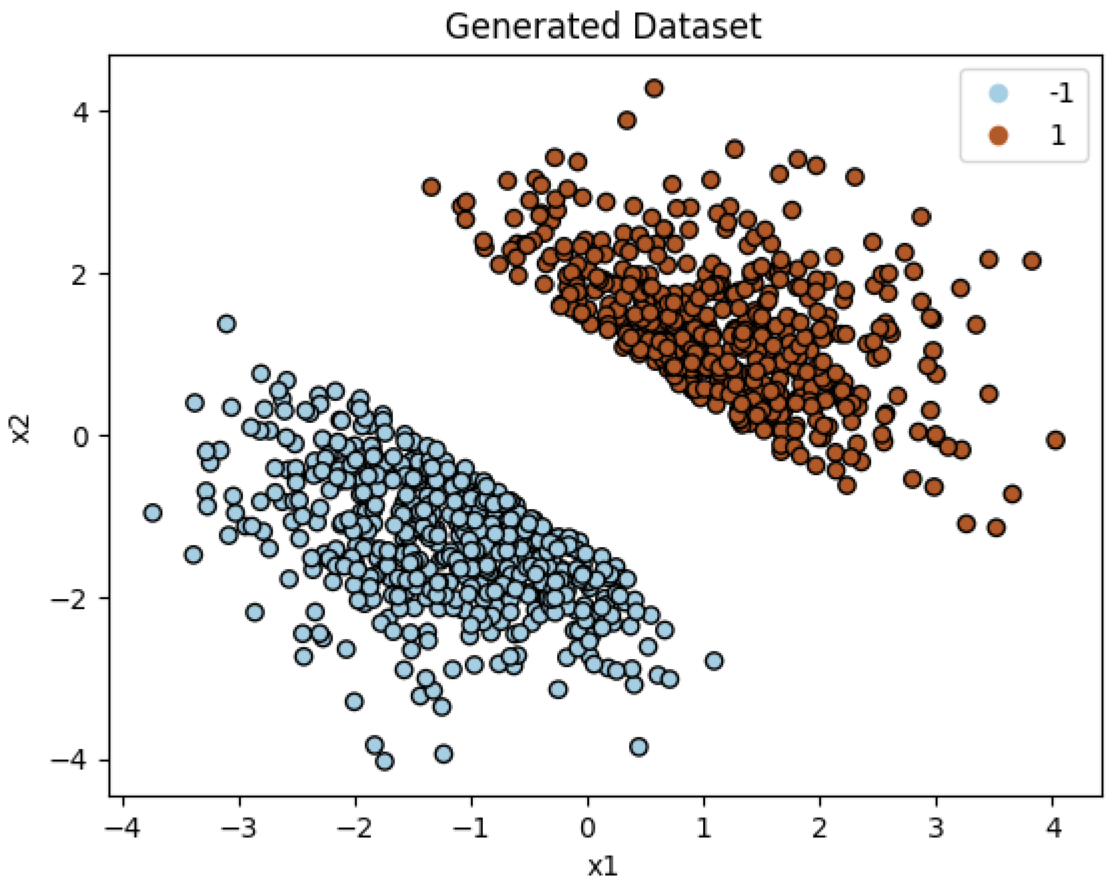
We can see that as the value of γ increases, the average number of epochs required to converge decreases. This is because as γ increases, the data becomes more and more linearly separable and hence the number of epochs required to converge decreases.

Q2

In [ ]:

```
# Create a Linearly separable 2D dataset
x, y = create_dataset_2(1000, 2)
scatter = plt.scatter(x[:, 0], x[:, 1], c=y, cmap=plt.cm.Paired, edgecolors='k')
xmin, xmax, ymin, ymax = plt.axis()
plt.legend(handles=scatter.legend_elements()[0], labels=["-1", "1"])
plt.xlabel("x1")
plt.ylabel("x2")
plt.title("Generated Dataset")
```

```
plt.show()

print("Percentage of -1 labels: ", (y == -1).sum().item() / len(y))
print("Percentage of 1 labels: ", (y == 1).sum().item() / len(y))
```




```
Percentage of -1 labels:  0.511
Percentage of 1 labels:  0.489
```

In [ ]:
```
x_train, y_train, x_test, y_test = split_dataset(x, y, 0.8)

# Append 1 to x for bias
x = torch.cat((x, torch.ones(x.shape[0], 1)), dim=1)
print("Shape of x: ", x.shape)
print("Shape of y: ", x.shape)
```

```
Shape of x:  torch.Size([1000, 3])
Shape of y:  torch.Size([1000, 3])
```

In [ ]:

```python
# Gradient Descent Algorithm for Hinge Loss
def hinge_gradient_descent(x, y, lr=0.1, max_epochs=100):
    w = torch.zeros(3)
    k = 0
    for epoch in range(max_epochs):
        nb_changes = 0
        for i in range(x.size(0)):
            if x[i].dot(w) * y[i] < 1:
                w = w + lr * (y[i]*x[i])
                nb_changes = nb_changes + 1
        if nb_changes == 0:
            # print('Stopping at Epoch: ', epoch)
            break
        k = k + 1
    # print('Number of changes: ', nb_changes)

    # return the weights and number of epochs
    return w, k

# Gradient Descent Algorithm for Log Loss
# def logistic_loss_gradient_descent(x, y, lr=0.1, max_epochs=100):
#     w = torch.zeros(3)
#     k = 0
#     for epoch in range(max_epochs):
#         nb_changes = 0
#         for i in range(x.size(0)):
#             if x[i].dot(w) * y[i] < 1:
#                 w = w + lr * (y[i]*x[i]) / (1 + torch.exp(y[i]*x[i].dot(w)))
#                 nb_changes = nb_changes + 1
#         if nb_changes == 0:
#             # print('Stopping at Epoch: ', epoch)
#             break
#         k = k + 1
#     # print('Number of changes: ', nb_changes)

#     # return the weights and number of epochs
#     return w, k

def logistic_loss_gradient_descent(x, y, lr=0.1, max_epochs=100):
    w = torch.zeros(3)
    k = 0
    for epoch in range(max_epochs):
        nb_changes = 0
```

```python
        for i in range(x.size(0)):
            y_pred = 1/(1 + torch.exp(-x[i].dot(w)))
            dL_dw = (y_pred - y[i]) * x[i]
            w = w - lr * dL_dw

            if np.linalg.norm(dL_dw) < 1e-4:
                break
        k = k + 1
    # print('Number of changes: ', nb_changes)

    # return the weights and number of epochs
    return w, k
```

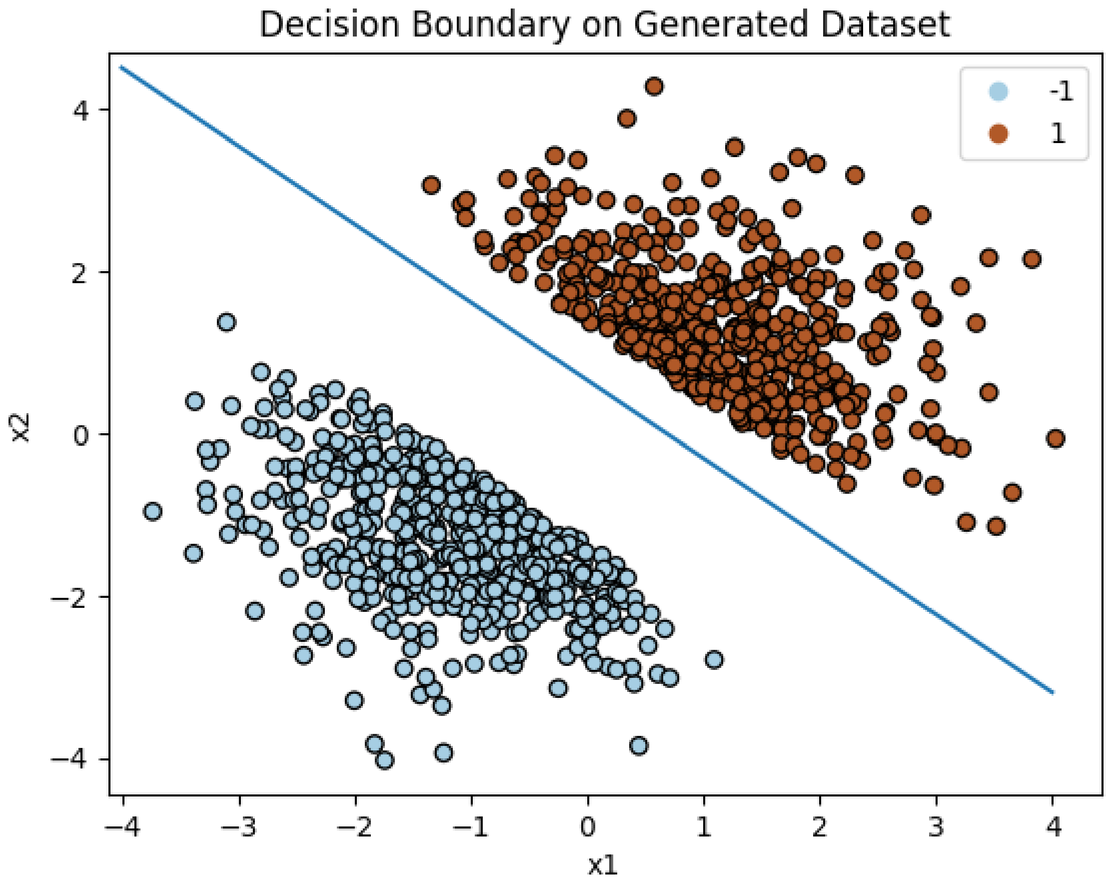
In [ ]:

```python
w, max_epochs = logistic_loss_gradient_descent(x, y, 0.1, 100)
print("W = ", w, " Max Epochs Run = ", max_epochs)
```

```
W =  tensor([ 4.0025,  4.1530, -2.7403])  Max Epochs Run =  100
```

In [ ]:

```python
# plot the decision boundary
x1 = np.linspace(-4, 4, 100)
x2 = -(w[0] * x1 + w[2]) / w[1]
plt.plot(x1, x2)
scatter = plt.scatter(x[:, 0], x[:, 1], c=y, cmap=plt.cm.Paired, edgecolors='k')
plt.xlim(xmin, xmax)
plt.ylim(ymin, ymax)
plt.legend(handles=scatter.legend_elements()[0], labels=["-1", "1"])
plt.xlabel("x1")
plt.ylabel("x2")
plt.title("Decision Boundary on Generated Dataset")
plt.show()

# print accuracy
# x_test = torch.cat((x, torch.ones(x_test.shape[0], 1)), dim=1)
y_pred = torch.sign(x @ w)
print("Accuracy = ", (torch.sum(y_pred == y) / y.shape[0]).item() * 100, "%")
```



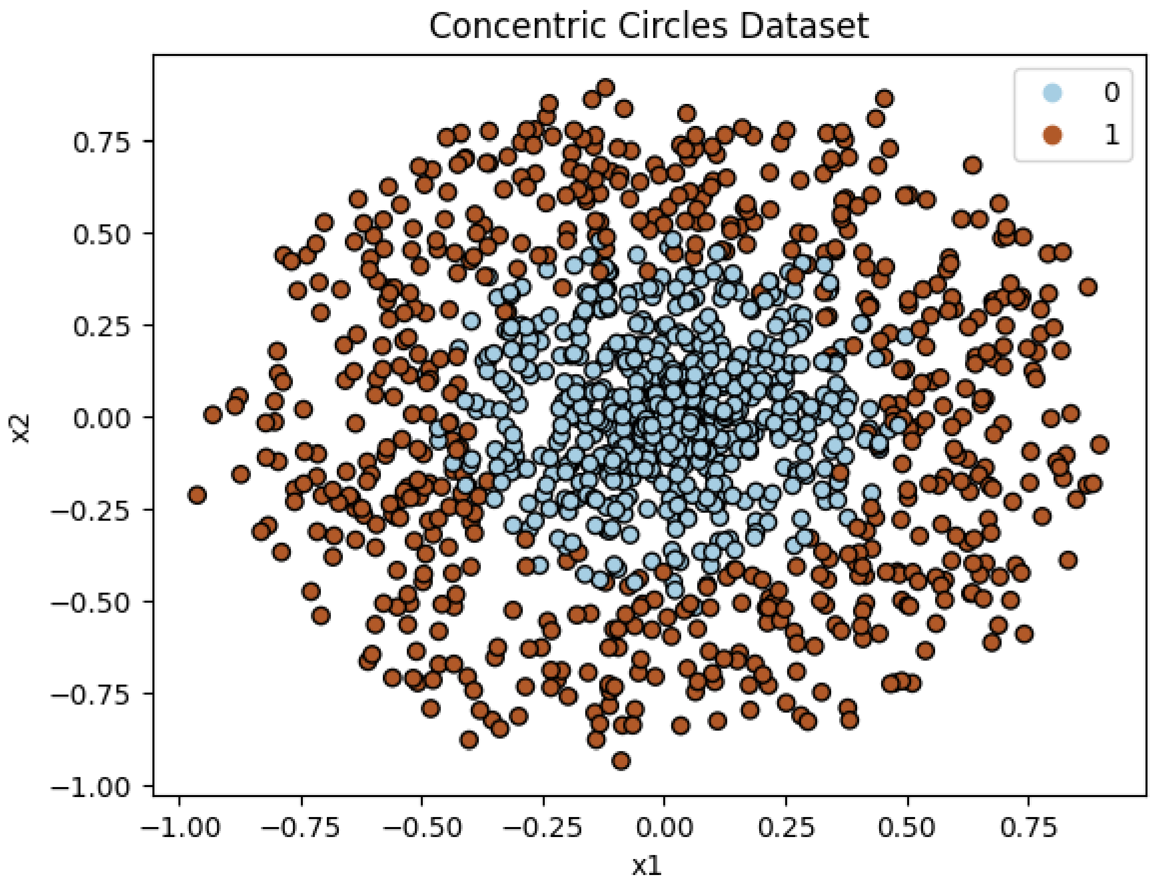

```
Accuracy =  100.0 %
```

Q3

In [ ]:

```
# create dataset with concentric circles
# import sklearn.datasets as skdata
from sklearn.datasets import make_circles

def create_concentric_dataset(n_samples, factor=0.9, noise=0.05):
    radius = np.random.rand(n_samples) * factor
    angle = np.random.rand(n_samples) * 2 * np.pi

    dataset = np.column_stack((radius * np.cos(angle), radius * np.sin(angle))) + np.random.normal(0, noise, (n_samples, 2))

    labels = np.zeros(n_samples)
```

```
    labels[radius > factor / 2] = 1

    return dataset, labels

x, y = create_concentric_dataset(n_samples=1250, factor=0.9, noise=0.05)
scatter = plt.scatter(x[:, 0], x[:, 1], c=y, cmap=plt.cm.Paired, edgecolors='k')
plt.title('Concentric Circles Dataset')
plt.xlabel('x1')
plt.ylabel('x2')
plt.legend(handles=scatter.legend_elements()[0], labels=["0", "1"])
plt.show()

print("Percentage of 0 labels: ", (y == 0).sum().item() / len(y))
print("Percentage of 1 labels: ", (y == 1).sum().item() / len(y))
```




```
Percentage of 0 labels:  0.5048
Percentage of 1 labels:  0.4952
```

In [ ]:
```
print(x.shape)
print(y.shape)
x = torch.from_numpy(x).float()
y = torch.from_numpy(y).float()

x_train, y_train, x_test, y_test = split_dataset(x, y, 0.8)
print("Shape of Training x: ", x_train.shape)
print("Shape of Training y: ", y_train.shape)
```

```
(1250, 2)
(1250,)
Shape of Training x:  torch.Size([1000, 2])
Shape of Training y:  torch.Size([1000])
```

In [ ]:
```
# Create MLP with 1 hidden layer from scratch
class MLP:
    def __init__(self, x, y, hidden_size=4, lr=0.1) -> None:
        self.x = x
        self.y = y
        self.input_size = x.shape[1]
        self.hidden_size = hidden_size
        self.output_size = 1
        self.lr = lr

        # Weights and Biases
        self.w1 = torch.randn(self.input_size, self.hidden_size)
        # print("w1: ",self.w1.shape)
        self.b1 = torch.randn(1) * torch.randn(self.hidden_size)
        # print("b1: ",self.b1.shape)
        self.w2 = torch.randn(self.hidden_size, self.output_size)
        # print("w2: ",self.w2.shape)
        self.b2 = torch.randn(1)


    # Signmoid Activation Function
    def sigmoid(self, x):
        return 1 / (1 + torch.exp(-x))

    # Signmoid Derivative
    def sigmoid_derivative(self, x):
        return x * (1 - x)

    # Hinge Loss Function
    def hinge_loss(self, y_pred, y):
```

```
        # print(y_pred.shape)
        # print(y.shape)
        # print((y_pred * y).shape)
        return torch.max(torch.zeros_like(y_pred), 1 - y_pred * y)

    # Square Loss Function
    def square_loss(self, y_pred, y):
        return (y_pred - y) ** 2

    # Hinge Loss Derivative
    def hinge_loss_derivative(self, y_pred, y):
        # print(y_pred.shape)
        # print(y.shape)
        return -y * (y * y_pred < 1)

    # Square Loss Derivative
    def square_loss_derivative(self, y_pred, y):
        return 2 * (y_pred - y)

    # Binary Cross Entropy Loss Function
    def binary_cross_entropy(self, y_pred, y):
        return - y * torch.log(y_pred) - (1 - y) * torch.log(1 - y_pred)

    # Binary Cross Entropy Loss Derivative
    def binary_cross_entropy_derivative(self, y_pred, y):
        return  -(y / y_pred) + ((1 - y) / (1 - y_pred))

    # Forward Propagation
    def forward(self, x):
        self.z1 = x @ self.w1 + torch.Tensor.repeat(self.b1, x.shape[0], 1)
        # print("z1: ",self.z1.shape)

        self.a1 = self.sigmoid(self.z1)
        # print("a1: ",self.a1.shape)

        self.z2 = self.a1 @ self.w2 + self.b2
        # print("z2: ",self.z2)

        self.a2 = self.sigmoid(self.z2)
        # print("a2: ",self.a2)

        # print("w2: ",self.w2)
        # print("w1: ",self.w1)
        return self.a2
```

```python
    # Backward Propagation
    def backward(self, x, y):
        y = y.reshape(-1, 1)
        # print("x shape: ", x.shape)

        self.loss_a2 = self.binary_cross_entropy(self.a2, y)
        # print("Loss_a2 shape: ", self.loss_a2.shape)

        # Calculate Gradients
        self.dL_d_a2 = self.binary_cross_entropy_derivative(self.a2, y)
        # print("dL_d_a2 shape: ", self.dL_d_a2.shape)

        self.da2_dz2 = self.sigmoid_derivative(self.a2)
        # print("da2_dz2 shape: ", self.da2_dz2.shape)

        self.dz2_d_w2 = self.a1.T
        # print("dz2_d_w2 shape: ", self.dz2_d_w2.shape)

        self.dz2_d_b2 = torch.ones_like(self.z2)
        # print("dz2_d_b2 shape: ", self.dz2_d_b2.shape)

        self.dL_d_w2 = self.dz2_d_w2 @ (self.dL_d_a2 * self.da2_dz2)
        # print("dL_d_w2 shape: ", self.dL_d_w2.shape)

        # self.dL_d_b2 = (self.dz2_d_b2 * (self.dL_d_a2.T @ self.da2_dz2)).reshape(-1)
        self.dL_d_b2 = ((self.dL_d_a2 * self.da2_dz2).T @ self.dz2_d_b2).reshape(-1)
        # print("dL_d_b2 shape: ", self.dL_d_b2.shape)

        self.da1_dz1 = self.sigmoid_derivative(self.a1)
        # print("da1_dz1 shape: ", self.da1_dz1.shape)

        self.dz1_dw1 = x
        # print("dz1_dw1 shape: ", self.dz1_dw1.shape)

        self.dz1_x = self.w1

        self.dz2_d_a1 = self.w2

        # print("dz2_d_a1 shape: ", self.dz2_d_a1.shape)
        # print("dz1_x shape: ", self.dz1_x.shape)
        # self.dz1_d_b1 = torch.ones_like(self.a1)
        # print("dz1_d_b1 shape: ", self.dz1_d_b1.shape)
```

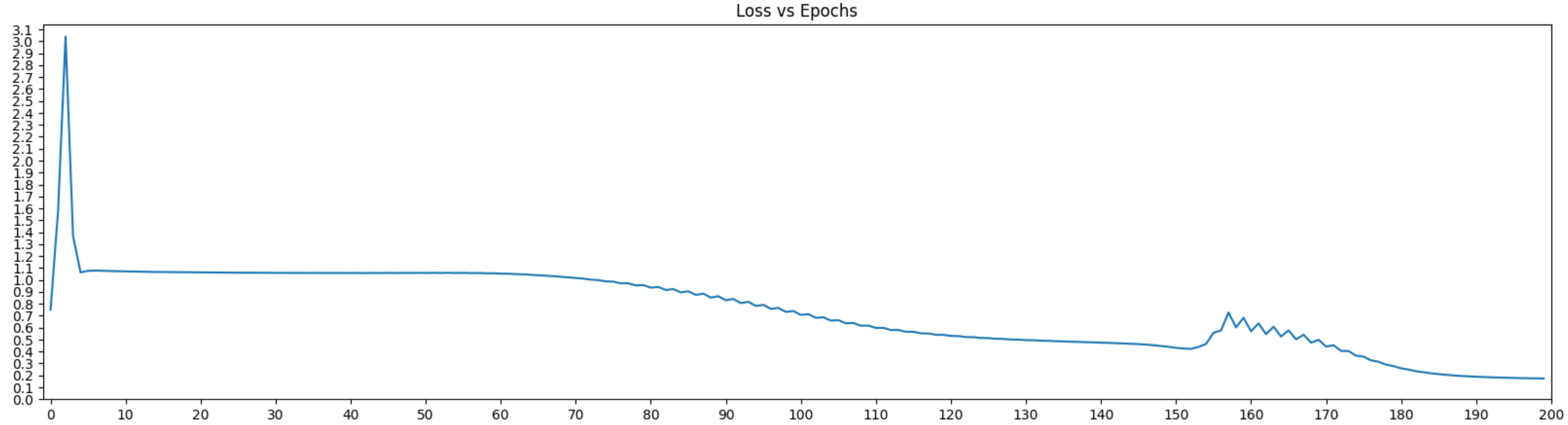
```
        # print("ter: ", ((self.dL_d_a2 * self.da2_dz2) @ self.w2.T).shape)
        self.dL_dw1 =  self.dz1_dw1.T @ (((self.dL_d_a2 * self.da2_dz2) @ self.w2.T) * self.da1_dz1)

        # print("dL_dw1 shape: ", self.dL_dw1.shape)
        # print("ter ",(((self.dL_d_a2 * self.da2_dz2) @ self.w2.T) @ self.da1_dz1.T).shape)
        # print((((self.dL_d_a2 * self.da2_dz2).T @ (self.da1_dz1 * self.dz1_d_b1))).T.shape)

        self.dL_db1 = (((self.dL_d_a2 * self.da2_dz2) @ self.w2.T) * self.da1_dz1).sum(axis=0)

        # print("dL_db1 shape: ", self.dL_db1.shape)

        # Updating Weights and Biases
        self.w2 -= self.lr * self.dL_d_w2
        self.b2 -= self.lr * self.dL_d_b2
        self.w1 -= self.lr * self.dL_dw1
        self.b1 -= self.lr * self.dL_db1


    # Training the Model
    def train(self, epochs=100):
        loss = []
        for epoch in range(epochs):
            self.forward(self.x)
            # print("W1 in forward: ", self.w1)
            # print("W2 in forward: ", self.w2)
            # print("B2 in forward: ", self.b2)
            # print("A2 in forward: ", self.a2)
            self.backward(self.x, self.y)
            # print("W1 in backward: ", self.w1)
            # print("W2 in backward: ", self.w2)
            # print("B2 in backward: ", self.b2)

            loss.append(self.loss_a2.mean())
            if epoch % 10 == 0:
                print("Epoch: ", epoch, " Loss: ", self.loss_a2.mean())
        # print("Final Predicted: ", self.forward(self.x))
        # print("Ground Truth: ", self.y)
        # print("z2: ", self.z2)

        # Plotting the Loss Curve
        plt.figure(figsize=(20, 5))
        plt.xticks(np.arange(0, epochs + 10, 10))
        plt.plot(loss)
        plt.xlim(-1, epochs)
```

```python
        plt.ylim(min(loss), max(loss) + 0.1)
        plt.yticks(np.arange(0, max(loss) + 0.1, 0.1))
        plt.title("Loss vs Epochs")
        plt.show()
        return

    def predict(self, x, threshold=0.5):
        predicted = self.forward(x)
        # print(torch.round(predicted))
        # apply threshold of 0.6 for label
        # print(predicted)

        return predicted > threshold


    def accuracy(self, x, y):
        # print(self.predict(x).shape)
        y = y.reshape(-1, 1)
        return torch.sum(self.predict(x) == y) / y.shape[0]
```

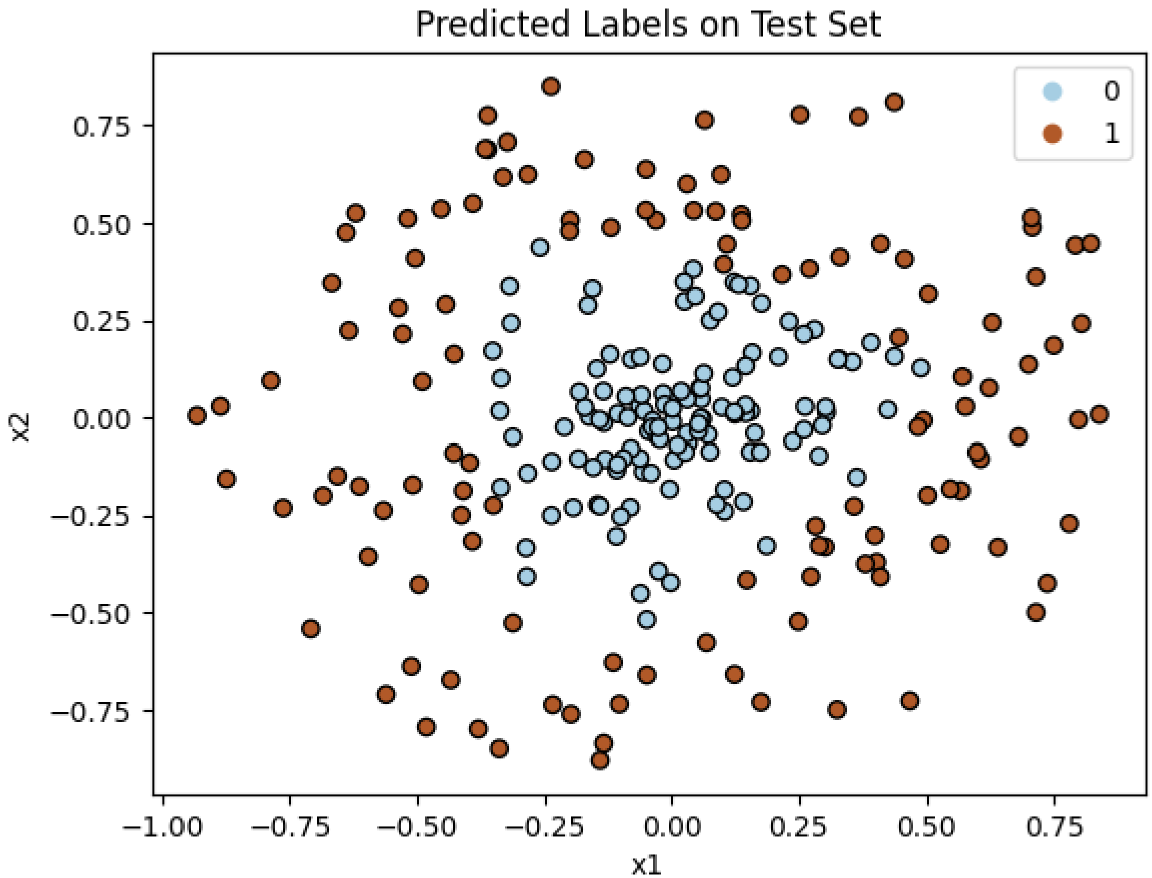
In [ ]:

```python
# create MLP
mlp = MLP(x_train, y_train, hidden_size=4, lr=0.01)
mlp.train(epochs=200)

print("Accuracy on Test set: ", mlp.accuracy(x_test, y_test).item() * 100, "%")
print("Accuracy on Training set: ", mlp.accuracy(x_train, y_train).item() * 100, "%")

# plot the predicted labels on the test set
scatetr = plt.scatter(x_test[:, 0], x_test[:, 1], c=mlp.predict(x_test).detach().numpy(),  cmap=plt.cm.Paired, edgecolors='k')
plt.legend(handles=scatetr.legend_elements()[0], labels=['0', '1'])
plt.xlabel("x1")
plt.ylabel("x2")
plt.title("Predicted Labels on Test Set")
plt.show()
```

```
Epoch:  0  Loss:  tensor(0.7497)
Epoch:  10  Loss:  tensor(1.0716)
Epoch:  20  Loss:  tensor(1.0629)
Epoch:  30  Loss:  tensor(1.0592)
Epoch:  40  Loss:  tensor(1.0579)
Epoch:  50  Loss:  tensor(1.0586)
Epoch:  60  Loss:  tensor(1.0531)
Epoch:  70  Loss:  tensor(1.0156)
Epoch:  80  Loss:  tensor(0.9359)
Epoch:  90  Loss:  tensor(0.8299)
Epoch:  100  Loss:  tensor(0.7074)
Epoch:  110  Loss:  tensor(0.5977)
Epoch:  120  Loss:  tensor(0.5305)
Epoch:  130  Loss:  tensor(0.4956)
Epoch:  140  Loss:  tensor(0.4744)
Epoch:  150  Loss:  tensor(0.4314)
Epoch:  160  Loss:  tensor(0.5697)
Epoch:  170  Loss:  tensor(0.4420)
Epoch:  180  Loss:  tensor(0.2593)
Epoch:  190  Loss:  tensor(0.1886)
```

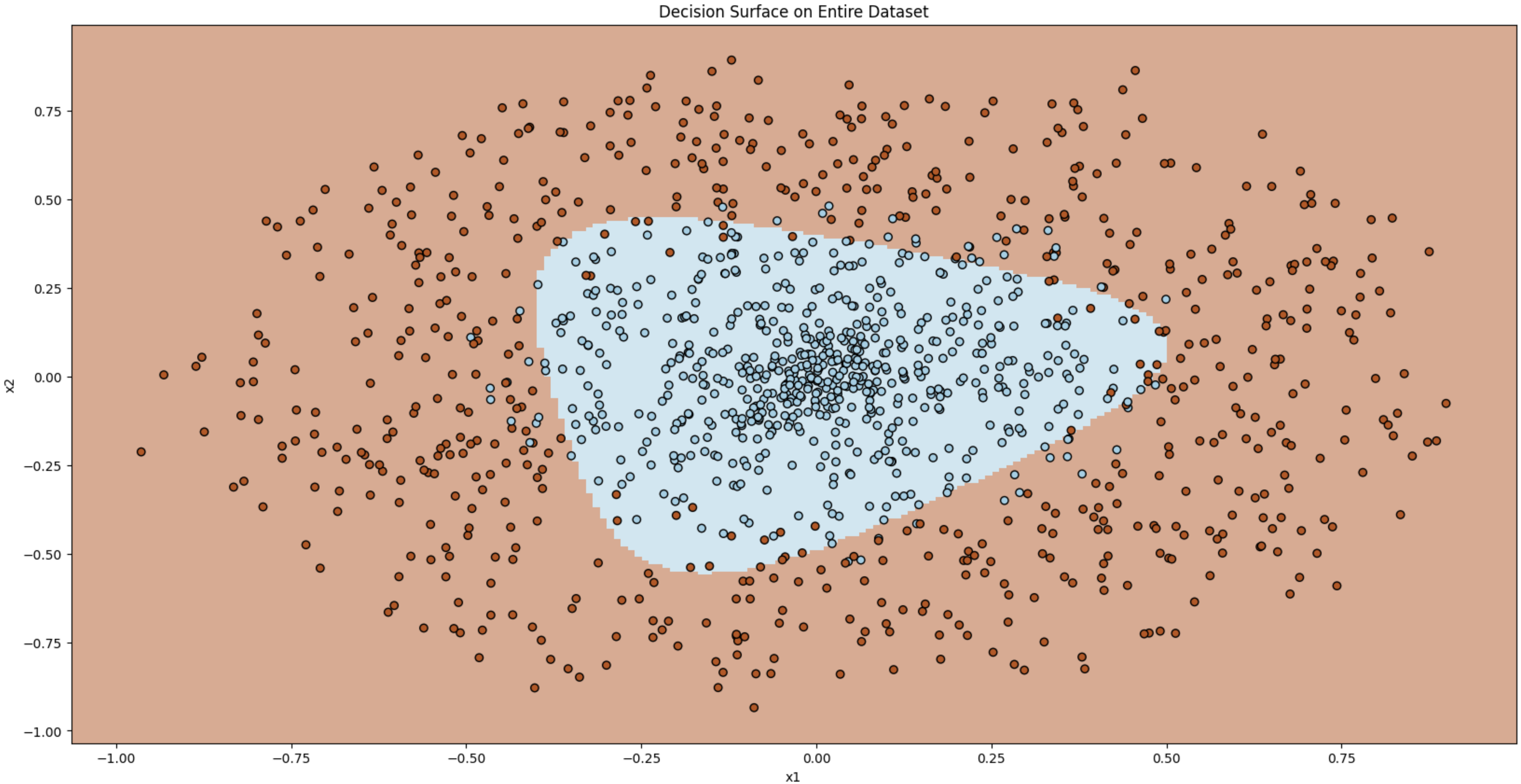



```
Accuracy on Test set:  92.40000247955322 %
Accuracy on Training set:  93.4000015258789 %
```



In [ ]:
```
# # Plot decision surface for MLP model on entire dataset

# x1_min, x1_max = x[:, 0].min() - 1, x[:, 0].max() + 1
# x2_min, x2_max = x[:, 1].min() - 1, x[:, 1].max() + 1

# x1_grid = np.arange(x1_min, x1_max, 0.01)
# x2_grid = np.arange(x2_min, x2_max, 0.01)

# x1_mesh, x2_mesh = np.meshgrid(x1_grid, x2_grid)

# x1_mesh_ = x1_mesh.flatten()
# x2_mesh_ = x2_mesh.flatten()

# x1_mesh_ = x1_mesh_.reshape((x1_mesh_.shape[0], 1))
# x2_mesh_ = x2_mesh_.reshape((x2_mesh_.shape[0], 1))
```

```python
# x_mesh = np.hstack((x1_mesh_, x2_mesh_))

# y_mesh = (mlp.predict(torch.from_numpy(x_mesh).float()).detach().numpy()).reshape(x1_mesh.shape)


# # plt.figure(figsize=(10, 10))
# plt.figure(figsize=(20, 10))
# plt.title("Decision Surface on Entire Dataset")
# plt.xlabel("x1")
# plt.ylabel("x2")
# plt.contourf(x1_mesh, x2_mesh, y_mesh.reshape(x1_mesh.shape), cmap=plt.cm.Paired, alpha=0.5)
# plt.scatter(x[:, 0], x[:, 1], c=y, cmap=plt.cm.Paired, edgecolors='k')
# plt.xlim(x[:, 0].min() - 0.1, x[:, 0].max() + 0.1)
# plt.ylim(x[:, 1].min() - 0.1, x[:, 1].max() + 0.1)
# plt.show()

x1_min, x1_max = x[:, 0].min() - 1, x[:, 0].max() + 1
x2_min, x2_max = x[:, 1].min() - 1, x[:, 1].max() + 1

x1_grid, x2_grid = np.mgrid[x1_min.item():x1_max.item():0.01, x2_min.item():x2_max.item():0.01]
# print(x1_grid.shape, x2_grid.shape)
x_mesh = np.array([x1_grid.flatten(), x2_grid.flatten()]).T
y_mesh = (mlp.predict(torch.from_numpy(x_mesh).float()).detach().numpy()).reshape(x1_grid.shape)

plt.figure(figsize=(20, 10))
plt.title("Decision Surface on Entire Dataset")
plt.xlabel("x1")
plt.ylabel("x2")
plt.pcolormesh(x1_grid, x2_grid, y_mesh, cmap=plt.cm.Paired, alpha=0.5)
plt.scatter(x[:, 0], x[:, 1], c=y, cmap=plt.cm.Paired, edgecolors='k')
plt.xlim(x[:, 0].min() - 0.1, x[:, 0].max() + 0.1)
plt.ylim(x[:, 1].min() - 0.1, x[:, 1].max() + 0.1)
plt.show()

# print accuracy on entire dataset
print("Accuracy on Entire Dataset: ", mlp.accuracy(x, y).item() * 100, "%")
```




```
Accuracy on Entire Dataset:  93.19999814033508 %
```

In [ ]: