medium

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URL of the dataset

```
spam_url = "https://hastie.su.domains/ElemStatLearn/datasets/spam.data"
# Load data
spam_data = read.table(spam_url, header = FALSE)
# View dataset structure
print(dim(spam_data))
## [1] 4601
              58
print(head(spam_data))
       V1
                 V3 V4
                         V5
                              V6
                                   V7
                                        8V
                                             V9 V10 V11 V12 V13 V14 V15
                     ## 1 0.00 0.64 0.64
## 2 0.21 0.28 0.50
                     0 0.14 0.28 0.21 0.07 0.00 0.94 0.21 0.79 0.65 0.21 0.14 0.14
## 3 0.06 0.00 0.71
                     0 1.23 0.19 0.19 0.12 0.64 0.25 0.38 0.45 0.12 0.00 1.75 0.06
## 4 0.00 0.00 0.00
                     0 0.63 0.00 0.31 0.63 0.31 0.63 0.31 0.31 0.31 0.00 0.00 0.31
## 5 0.00 0.00 0.00
                     0 0.63 0.00 0.31 0.63 0.31 0.63 0.31 0.31 0.31 0.31 0.00 0.00 0.31
## 6 0.00 0.00 0.00
                     0 1.85 0.00 0.00 1.85 0.00 0.00 0.00 0.00 0.00 0.00 0.00
                     V20
                          V21 V22
                                   V23
                                        V24 V25 V26 V27 V28 V29 V30 V31 V32 V33
## 1 0.00 1.29 1.93 0.00 0.96
                                0 0.00 0.00
                                                  0
                                                               0
                                                                       0
                                              0
                                                      0
                                                                  0
## 2 0.07 0.28 3.47 0.00 1.59
                                0 0.43 0.43
                                              0
                                                  0
                                                      0
                                                          0
                                                               0
                                                                  0
## 3 0.06 1.03 1.36 0.32 0.51
                                0 1.16 0.06
                                                      0
                                                              0
                                                                               0
                                              0
                                                  0
                                                          0
                                                                  0
                                                                       0
                                                                           0
## 4 0.00 0.00 3.18 0.00 0.31
                                                      0
                                0 0.00 0.00
                                              0
                                                  0
                                                                               0
## 5 0.00 0.00 3.18 0.00 0.31
                                0 0.00 0.00
                                                  0
                                                      0
                                                          0
                                                               0
                                                                  0
                                                                       0
                                                                           0
                                                                               0
                                              0
  6 0.00 0.00 0.00 0.00 0.00
                                                      0
                                0 0.00 0.00
                                              0
                                                  0
                                                          0
                                                               0
                                                                  0
                                                                       0
                                                                               0
##
     V34 V35 V36 V37 V38 V39
                               V40 V41 V42
                                            V43 V44
                                                     V45
                                                          V46 V47 V48
                                                                       V49
                                                                              V50
## 1
       0
               0 0.00
                        0
                            0 0.00
                                         0 0.00
                                                  0 0.00 0.00
                                                                     0 0.00 0.000
## 2
               0 0.07
                            0 0.00
                                         0 0.00
                                                  0 0.00 0.00
                                                                     0 0.00 0.132
       0
           0
                        0
                                     0
                                                                0
## 3
       0
           0
               0 0.00
                        0
                            0 0.06
                                     0
                                         0 0.12
                                                  0 0.06 0.06
                                                                0
                                                                     0 0.01 0.143
                            0 0.00
## 4
           0
               0 0.00
                                         0 0.00
                                                  0 0.00 0.00
                                                                     0 0.00 0.137
## 5
               0 0.00
                            0 0.00
                                         0 0.00
                                                  0 0.00 0.00
                                                                     0 0.00 0.135
       0
           0
                        0
                                     0
                                                                0
##
  6
       0
           0
               0 0.00
                        0
                            0 0.00
                                         0 0.00
                                                  0 0.00 0.00
                                                                0
                                                                     0 0.00 0.223
     V51
           V52
                             V55 V56
                                      V57 V58
##
                 V53
                       V54
       0 0.778 0.000 0.000 3.756
## 2
       0 0.372 0.180 0.048 5.114 101 1028
## 3
       0 0.276 0.184 0.010 9.821 485
       0 0.137 0.000 0.000 3.537
## 4
                                      191
                                            1
       0 0.135 0.000 0.000 3.537
                                      191
       0 0.000 0.000 0.000 3.000
## 6
                                       54
                                            1
```

```
# Convert to matrix
data_matrix = as.matrix(spam_data[, -ncol(spam_data)])
labels = as.numeric(spam_data[, ncol(spam_data)]) + 1 # Shift all labels up by 1
# Normalize data (zero mean, unit variance)
data_mean = colMeans(data_matrix)
data_sd = apply(data_matrix, 2, sd)
data_matrix = scale(data_matrix, center = data_mean, scale = data_sd)
# Convert to torch tensors
data_tensor = torch_tensor(data_matrix, dtype = torch_float())
labels_tensor = torch_tensor(labels, dtype = torch_long())
# Define a dataset class for Spam Data
spam_dataset = dataset(
  name = "SpamDataset",
  initialize = function(x, y) {
    self$data = x # Ensure it's a tensor
    self$labels = y # Ensure labels are tensors
  },
  .getitem = function(index) {
   list(
     x = self$data[index, ], # Ensure features remain a tensor
     y = self$labels[index] # Labels remain a tensor
  },
  .length = function() {
    self$data$shape[1] # Returns number of samples
  }
)
# Initialize the dataset with torch tensors
dataset = spam_dataset(data_tensor, labels_tensor)
# Print dataset details
cat("Dataset length:", dataset$.length(), "\n")
## Dataset length: 4601
# Print a sample to verify structure
print(dataset$.getitem(1))
## $x
## torch_tensor
## -0.3424
## 0.3308
## 0.7128
## -0.0469
## 0.0116
```

```
## -0.3502
## -0.2918
## -0.2625
## -0.3233
## -0.3713
## -0.2968
## 0.1141
## -0.3120
## -0.1749
## -0.1901
## 0.0862
## -0.3211
## 2.0810
## 0.1509
## -0.1679
## 0.1251
## -0.1182
## -0.2902
## -0.2130
## -0.3288
## -0.2992
## -0.2279
## -0.2318
## -0.1667
## -0.2252
## ... [the output was truncated (use n=-1 to disable)]
## [ CPUFloatType{57} ]
##
## $y
## torch_tensor
## 2
## [ CPULongType{} ]
# Split into training (80%) and testing (20%)
# Define batch size and dataloader
batch_size = 32
dataloader = dataloader(dataset, batch_size = batch_size, shuffle = TRUE)
net = nn_module(
  "SpamNet",
  initialize = function() {
    self$fc1 = nn_linear(ncol(data_matrix), 128) # More neurons
    self fc2 = nn_linear(128, 64)
    self$fc3 = nn_linear(64, 2) # Output layer (2 classes)
    self$dropout = nn_dropout(p = 0.3) # Dropout for regularization
  },
  forward = function(x) {
    x %>%
      self$fc1() %>%
     nnf_relu() %>%
      self$dropout() %>%
      self$fc2() %>%
     nnf_relu() %>%
```

```
self$dropout() %>%
      self$fc3() %>%
     nnf_log_softmax(dim = 1) # Apply log-softmax for classification
 }
)
# Initialize model
model = net()
# Define optimizer (SGD with learning rate)
optimizer = optim_adam(model$parameters, lr = 0.001)
num_epochs = 20  # More epochs for better learning
for (epoch in 1:num_epochs) {
  losses = c()
  coro::loop(for (batch in dataloader) {
   optimizer$zero_grad() # Reset gradients
   output = model(batch$x) # Forward pass
   loss = nnf_nll_loss(output, batch$y) # Compute loss
   loss$backward() # Backpropagation
   optimizer$step() # Update model parameters
   losses = c(losses, loss$item()) # Store loss for reporting
  })
  # Print loss for each epoch
  cat(sprintf("Epoch %d: Loss = %.4f\n", epoch, mean(losses)))
## Epoch 1: Loss = 3.1979
## Epoch 2: Loss = 3.0416
## Epoch 3: Loss = 3.0045
## Epoch 4: Loss = 2.9870
## Epoch 5: Loss = 2.9756
## Epoch 6: Loss = 2.9696
## Epoch 7: Loss = 2.9640
## Epoch 8: Loss = 2.9511
## Epoch 9: Loss = 2.9512
## Epoch 10: Loss = 2.9479
## Epoch 11: Loss = 2.9405
## Epoch 12: Loss = 2.9398
## Epoch 13: Loss = 2.9339
## Epoch 14: Loss = 2.9359
## Epoch 15: Loss = 2.9239
## Epoch 16: Loss = 2.9241
## Epoch 17: Loss = 2.9152
## Epoch 18: Loss = 2.9161
## Epoch 19: Loss = 2.9115
## Epoch 20: Loss = 2.9202
```

R Markdown

Steps Involved

- 1. Dataset Loading: Downloaded and processed the Spam dataset from the UCI ML Repository.
- 2. Data Preprocessing:
- Converted it into a matrix.
- Applied normalization (zero mean, unit variance).
- Converted it into torch tensors.
- 3. Dataset Handling: Implemented a custom dataset class (spam_dataset) for structured data processing.
- 4. Batch Processing: Used torch dataloaders to efficiently load batches.
- 5. Model Training:
- Implemented a 3-layer neural network with:
- ReLU activations.
- Dropout for regularization.
- Log-softmax for classification.
- Optimized with Adam optimizer.
- $\bullet~$ Trained for 20 epochs, tracking the loss.