

# Practice Problems for PyTorch. Advanced Machine Learning

1. You are working on a classification problem with 10 input variables and 3 output classes.

(a) Write a model in PyTorch using `torch.nn.Sequential` that includes a Softmax at the end. Why might this cause issues with standard cross-entropy?

```
import torch
import torch.nn as nn

# Here we explicitly add a final Softmax
model = nn.Sequential(
    nn.Linear(10, 16),
    nn.ReLU(),
    nn.Linear(16, 3),
    nn.Softmax(dim=1) # final activation
)

#you also could just do multiclass logistic reg instead of a NN
model = nn.Sequential(
    nn.Linear(10, 3),
    nn.Softmax(dim=1) # final activation
)
```

(b) Write a training loop for this model in PyTorch.

```
def train_model(model, optimizer, train_dl, epochs=10):
    # Instead of CrossEntropyLoss (which expects raw logits),
    # we'll use NLLLoss, which expects log probabilities.
    criterion = nn.NLLLoss()

    for epoch in range(epochs):
        model.train() # put model in training mode
        total_samples = 0
        sum_loss = 0.0

        for x_batch, y_batch in train_dl:
            optimizer.zero_grad()

            # Forward pass: model(...) now returns probabilities
            # because our model ends with Softmax(dim=1).
            probs = model(x_batch)

            # "Undo" the softmax by taking log(probabilities).
            # Add a small epsilon to avoid log(0.0).
            log_probs = torch.log(probs + 1e-8)

            # NLLLoss expects log probabilities.
            loss = criterion(log_probs, y_batch)

            loss.backward()
            optimizer.step()

            # Bookkeeping
            batch_size = y_batch.size(0)
            total_samples += batch_size
            sum_loss += loss.item() * batch_size

        train_loss = sum_loss / total_samples
        print(f"Epoch{epoch+1}/{epochs}, Loss:{train_loss:.4f}")

    return model
```

**Why is this needed?** If we used `CrossEntropyLoss` directly on the model's output, it would run *another* log-softmax internally. This is generally not what we want when our model already outputs a softmax. Instead, we "undo" the softmax by taking the log ourselves, and feed that into `NLLLoss`, which expects log probabilities.

**2. Write a function that, given a model and a data loader, computes balanced accuracy.**  
Assume you have a binary classification problem.

```
import numpy as np
from sklearn.metrics import balanced_accuracy_score

def compute_balanced_accuracy(model, data_loader):
    model.eval()
    all_preds = []
    all_labels = []

    with torch.no_grad():
        for x, y in data_loader:
            probs = model(x)
            # Since we use Softmax, 'probs' are probs.
            # For multi-class, we pick class argmax either way:
            preds = torch.argmax(probs, dim=1)
            # .cpu() moves the tensor from GPU memory to CPU memory
            # so we can convert it to a NumPy array with .numpy()
            all_preds.append(preds.cpu().numpy())
            all_labels.append(y.cpu().numpy())

    all_preds = np.concatenate(all_preds)
    all_labels = np.concatenate(all_labels)

    # Compute balanced accuracy
    return balanced_accuracy_score(all_labels, all_preds)
```

**3. What is the shape of the tensor `out` in the following code?**

```
embed = nn.Embedding(5, 7)
x = torch.LongTensor([[1,0,1,4,2,1]])
out = embed(x)
```

The embedding dimension is 7, and the input `x` has shape (1, 6). Thus:

$$(1, 6, 7).$$

**4. What is the value of the tensor `x.grad` after running the next few lines?**

```
x = torch.tensor([1, 3, 2], requires_grad=True)
L = (3*x + 7).sum()
L.backward()
```

$$L = \sum_i (3x_i + 7).$$

Thus the gradient of  $L$  w.r.t. each  $x_i$  is 3, so:

$$x.grad = [3, 3, 3].$$

**5. Create the following tensors with shape  $(2, 2, 2)$ : all zeros, all ones, and random with normal distribution.**

```
# All zeros
t1 = torch.zeros((2, 2, 2))

# All ones
t2 = torch.ones((2, 2, 2))

# Random with normal distribution
t3 = torch.randn((2, 2, 2))
```

**6. Describe what each of the following lines of code are doing during a training loop:**

- `loss.backward()`:
  - Calculates gradients of `loss` with respect to  $x$ .
  - The gradients are stored in `param.grad` for each parameter.
- `optimizer.step()`:
  - Updates the parameters based on the gradients computed by `loss.backward()`.