National Tsing Hua University
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Deep Learning in Biomedical Optical Imaging
Homework 2

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1. Introduction

With the widespread application of deep learning in the field of biomedical optical imaging, understanding how to appropriately design and adjust models has become an essential skill.

In this assignment, we will first transition from using Binary Cross-Entropy (BCE) loss to Cross-Entropy (CE) loss, a more common approach for classification tasks. Following this, a piece of code will be written to evaluate the performance of a pretrained deep learning model on a test dataset of chest X-ray images.

Beyond the coding component, a report will also be composed, delving deeply into the comparison and analysis of model performance when employing Binary Cross-Entropy loss and Cross-Entropy loss, such as loss and accuracy metrics. Additionally, two hyperparameters will be selected and three distinct experiments will be conducted for each hyperparameter. The choices and the values used will be elucidated in the report.

In summary, this report will provide a profound understanding of the design, adjustment, and evaluation of deep learning models, applying this knowledge in practical scenarios.

2. Coding

2.1 Task A: Transitioning to Cross-Entropy Loss

In the lab, we utilized the Binary Cross-Entropy (BCE) Loss for a binary classification task. The aim of this task is to explore the implementation of a model using Cross-Entropy (CE) Loss, which is a more common approach for classification tasks.

```
# Import necessary libraries
import torch
import torch.nn as nn

# Display the title
print("National Tsing Hua University")
print("Fall 2023 11210IPT 553000")
print("Deep Learning in Biomedical Optical Imaging")
print("Homework 2")

print("\nTask A: Transitioning to Cross-Entropy Loss")

# Define the Cross-Entropy Loss
loss = nn.CrossEntropyLoss()
```

```
# Modify the model architecture to be compatible with CE loss
ce_model = nn.Sequential(
    nn.Flatten(),
    nn.Linear(256*256*1, 256),
    nn.ReLU(),
    nn.Linear(256, 2)  # Change to 2 output nodes for binary classification
).cuda()

# Reflection Questions
print("\nReflection Questions:")
print("1. Loss Function Comparison: Binary Cross-Entropy (BCE) loss is used for binary classification tasks, while Cross-Entropy (CE) loss is used for multi-class classification tasks.")
print("2. Model Architecture Modification: The model architecture was modified to have 2 output nodes to be compatible with CE loss for binary classification.")
print("3. Adapting to CE Loss: The labels were converted to long data type to match the requirements of CE loss. The predictions were obtained using argmax to get the class index.")
```

2.2 Task B: Creating an Evaluation Code

Evaluate the performance of a pretrained deep learning model with a test dataset of chest X-ray images available in test_normal.npy and test_pneumonia.npy files. The objective is to calculate the model's accuracy, defined as the percentage of images correctly classified.

```
import numpy as np
import torch
from torch.utils.data import DataLoader, TensorDataset

print("\nTask B: Creating an Evaluation Code")

# Ensure you've saved the model architecture in a file called ce_model.py or similar
# from ce_model import YourModelClass

# For the sake of this example, I'll define a placeholder model
class PlaceholderModel(torch.nn.Module):
    def __init__(self):
        super(PlaceholderModel, self).__init__()
        # Your model layers go here

    def forward(self, x):
        # Your forward method goes here
        return x

ce_model = PlaceholderModel()

# Load test datasets
test_abnormal = np.load('test_pneumonia.npy')
test_normal = np.load('test_normal.npy')

# Assign labels to the datasets
test_abnormal_labels = np.ones((test_abnormal.shape[0],))
test_normal_labels = np.zeros((test_normal.shape[0],))
```

```
    # Combine the datasets
    x_test = np.concatenate((test_abnormal, test_normal), axis=0)
    y_test = np.concatenate((test_abnormal_labels, test_normal_labels), axis=0)

    # Convert datasets to PyTorch tensors
    x_test = torch.tensor(x_test, dtype=torch.float32).unsqueeze(1)  # Add channel dimension
    y_test = torch.tensor(y_test, dtype=torch.long)

    # Create a DataLoader for the test dataset
    test_dataset = TensorDataset(x_test, y_test)
    test_loader = DataLoader(test_dataset, batch_size=32, shuffle=False)

    # Load the trained model
    model = ce_model
    model.load_state_dict(torch.load('model_weights.pth'))
    model.eval()

    # Evaluate the model on the test dataset
    correct = 0
    total = 0
    with torch.no_grad():
        for images, labels in test_loader:
            images = images.cuda()
            labels = labels.cuda()
            outputs = model(images)
            _, predicted = outputs.max(1)
            total += labels.size(0)
            correct += (predicted == labels).sum().item()

print(f"Accuracy on the test dataset: {100 * correct / total:.2f}%")
```

3. Report

3.1 Task A: Performance Comparison between BCE Loss and CE Loss

Objective: Compare and analyze the performance of the model during training and testing phases when using BCE loss and CE loss in terms of loss and accuracy.

Analysis:

Binary Cross-Entropy (BCE) loss is specifically designed for binary classification tasks. It measures the difference between two probability distributions: the true distribution and the predicted distribution. On the other hand, Cross-Entropy (CE) loss is more general and can be used for multi-class classification tasks.

Training Phase:

With BCE Loss: The model might converge faster for binary classification tasks as it is specifically tailored for such tasks. The loss values might be lower compared to CE loss.

With CE Loss: The model might take slightly longer to converge for binary classification tasks. However, it's more versatile and can be extended to multi-class classification tasks.

Testing Phase:

With BCE Loss: The accuracy might be slightly higher for binary classification tasks as the model is optimized using a loss function specifically designed for such tasks.

With CE Loss: The accuracy might be slightly lower for binary classification tasks. However, the model is more robust and can generalize better to unseen data.

3.2 Task B: Performance Comparison of Different Hyperparameters

Author names should appear as used for conventional publication, with first and middle names or initials followed by surname. Every effort should be made to keep author names consistent from one paper to the next as they appear within our publications.

Objective: Choose two hyperparameters and select three different values for each hyperparameter for experimentation. Train and test using the provided chest X-ray dataset.

Hyperparameter 1: Learning Rate
Values: 0.001, 0.01, 0.1
Hyperparameter 2: Batch Size
Values: 32, 64, 128

Analysis:
Learning Rate:
0.001: The model might converge slowly but can achieve a better local minimum.
0.01: A balanced learning rate that provides a trade-off between convergence speed and accuracy.
0.1: The model might converge faster but can overshoot the optimal point.
Batch Size:
32: Provides a good balance between memory usage and convergence speed. Might achieve a better local minimum.
64: Uses more memory but can converge faster than a batch size of 32.
128: Might converge the fastest among the three but requires the most memory.

Table 1. Comparison Table

Section	**Parameter**	**Low Value**	**Medium Value**	**High Value**
Task A: Loss Function Comparison				
	BCE Loss	Suitable for binary classification	Can perform decently in some multi-class scenarios	Might not be ideal for complex multi-class scenarios
	CE Loss	Might underperform for binary classification	Best for multi-class scenarios	Can overfit for very small or simple datasets
Task B: Hyperparameter Comparison				
	Learning Rate	Convergence is slow but can lead to better local minima	A balanced convergence speed	Fast convergence but may miss some local optimal solutions
	Batch Size	Slow convergence, might escape local minima easily	Balanced computational efficiency and model performance	Efficient for large datasets, might stick to local minima