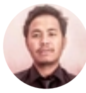

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Fine-Tuning a Pre-Trained Model in PyTorch: A Step-by-Step Guide for Beginners

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Fine-tuning is a powerful technique that allows you to adapt a pre-trained model to a new task, saving time and resources. This tutorial will guide you through fine-tuning a ResNet18 model for digit classification using PyTorch.

Step 1: Setting Up the Environment and Model

First, let's import the required libraries and set up the pre-trained model.

```
import torch
import torch.nn as nn
import torch.optim as optim
import torchvision
import torchvision.transforms as transforms
from torchvision import models

# Load a pre-trained ResNet18 model
```

```
model = models.resnet18(pretrained=True)

# Modify the last layer to match MNIST classes (10 classe
model.fc = nn.Linear(model.fc.in_features, 10)

# Set the model to training mode and use GPU if availabl
device = torch.device("cuda" if torch.cuda.is_available(
model = model.to(device)
```

Explanation: We are using ResNet18, which is pre-trained on ImageNet. The last layer is modified to fit our new task (10 classes for digits 0-9).

Step 2: Preparing the Dataset

We need to resize the MNIST images to 224x224 because ResNet18 expects this size.

```
# Transform images to 224x224 and normalize
transform = transforms.Compose([
    transforms.Resize(224),
    transforms.ToTensor(),
    transforms.Normalize((0.5,), (0.5,))
])

# Load the MNIST dataset
trainset = torchvision.datasets.MNIST(root='./data', tra
trainloader = torch.utils.data.DataLoader(trainset, batc

testset = torchvision.datasets.MNIST(root='./data', trai
testloader = torch.utils.data.DataLoader(testset, batch_
```

Explanation: We resize images and normalize them to fit what the *model expects. We also create data loaders for training and testing.*

Step 3: Setting Up the Loss Function and Optimizer

Define the loss function and optimizer. We use Adam, a popular choice for fine-tuning.

```
# Define loss function and optimizer
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=0.001)

# Learning rate scheduler to adjust the learning rate
scheduler = optim.lr_scheduler.StepLR(optimizer, step_si
```

Explanation: CrossEntropyLoss is used for classification tasks, and Adam is chosen for optimization. The scheduler helps adjust the learning rate during training.

Step 4: Fine-Tuning the Model

Train the model for a few epochs to fine-tune it on the new task.

```
# Fine-tune the model
num_epochs = 5
#set num_epochs to a smaller number like 1 and use T4 GPU
for epoch in range(num_epochs):
    running_loss = 0.0
    for images, labels in trainloader:
        images, labels = images.to(device), labels.to(dev

        optimizer.zero_grad()
        outputs = model(images)
        loss = criterion(outputs, labels)
        loss.backward()
        optimizer.step()
```

```
            running_loss += loss.item()

        # Step the scheduler after each epoch
        scheduler.step()

        print(f"Epoch [{epoch+1}/{num_epochs}], Loss: {runni

    print('Fine-tuning complete!')
```

Explanation: We loop through the dataset, perform forward and backward passes, and update the model's weights. This step adapts the pre-trained model to our specific task.

Step 5: Saving the Fine-Tuned Model
Save the fine-tuned model for later use.

```
# Save the fine-tuned model
torch.save(model.state_dict(), 'finetuned_resnet18_mnist
print('Model saved!')
```

Explanation: We save the model's state dictionary (parameters) to a file. This allows us to load it later without retraining.

Step 6: Evaluating the Model
Check how well the model performs on unseen data.

```
# Set the model to evaluation mode
model.eval()

correct = 0
total = 0
```

```
with torch.no_grad():
    for images, labels in testloader:
        images, labels = images.to(device), labels.to(dev
        outputs = model(images)
        _, predicted = torch.max(outputs.data, 1)
        total += labels.size(0)
        correct += (predicted == labels).sum().item()

print(f'Accuracy of the fine-tuned model on the test ima
```

Explanation: We set the model to evaluation mode and calculate accuracy on the test set to see how well the model generalizes to new data.

Step 7: Making Predictions
Finally, use the fine-tuned model to make predictions on a single image.

```
# Load the model for inference
model = models.resnet18()
model.fc = nn.Linear(model.fc.in_features, 10)
model.load_state_dict(torch.load('finetuned_resnet18_mni
model.eval()
model = model.to(device)

# Make a prediction on a single image from the test set
test_image, _ = testset[0]  # Get the first image from th
test_image = test_image.unsqueeze(0).to(device)  # Add a

output = model(test_image)
_, predicted = torch.max(output, 1)

print('Predicted label:', predicted.item())
```

Explanation: We load the saved model, set it to evaluation mode, and use it to predict the class of a new image.

Conclusion

Fine-tuning is an efficient way to adapt powerful pre-trained models to new tasks with minimal effort. In this guide, you learned how to:

1.Set up a pre-trained model and modify it for a new task.
2.Prepare and load your dataset.
3.Train and fine-tune the model with a new dataset.
4.Save and load the model for future use.
5.Make predictions using the fine-tuned model.

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Thank you!

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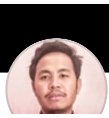

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