attention

July 2, 2024

1 Exercise 11 Part 1: Self-Attention

Summer Semester 2024

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1.0.1 Task: Implement Self-Attention

In this exercise, you will implement multi-head self-attention for a 2D sequence of tokens (shape `B D H W`) yourself using **only basic functions (no pre-made attention implementations!)**. You're allowed to use simple functions such as, e.g., `torch.bmm()`, `torch.nn.functional.softmax()`, … and simple modules such as `torch.nn.Linear`.

Usage of functions provided by the `einops` library (such as `einops.rearrange()`) is also allowed and encouraged (but completely optional!), as it allows writing the code in a nice and concise way by specifying operations across axes of tensors as strings instead of relying on dimension indices. A short introduction into einops is available at https://nbviewer.org/github/arogozhnikov/einops/blob/master/docs/1-einops-basics.ipynb.

[ ]:
```
import math

import torch
import torch.nn as nn
import torch.nn.functional as F

# Optional
import einops

device = 'mps' if torch.backends.mps.is_available() else ('cuda' if torch.cuda.
 ↪is_available() else 'cpu')
print(f'Using device "{device}".')
```

```
Using device "cuda".
```

[ ]:
```
class SelfAttention2d(nn.Module):
    def __init__(
        self,
        embed_dim: int = 256,
        head_dim: int = 32,
        value_dim: int = 32,
        num_heads: int = 8,
    ):
        """Multi-Head Self-Attention Module with 2d token input & output

        Args:
            embed_dim (int, optional): Dimension of the tokens at the input &␣
↪output. Defaults to 256.
            head_dim (int, optional): Per-head dimension of query & key.␣
↪Defaults to 32.
            value_dim (int, optional): Per-head dimension of values. Defaults␣
↪to 32.
            num_heads (int, optional): Number of attention heads. Defaults to 6.
        """
        super().__init__()

        # TODO: Student.
        # Hint: use a single linear layer for q/k/v/out each, and name the␣
↪respective layers q, k, v, out for the unit tests below to work.
        self.embed_dim = embed_dim
        self.head_dim = head_dim
        self.value_dim = value_dim
        self.num_heads = num_heads

        #assert(self.head_dim * num_heads == embed_dim), "Embed size needs to␣
↪be divided by heads"


        self.q = nn.Linear(embed_dim, head_dim * num_heads, bias=False)
        self.k = nn.Linear(embed_dim, head_dim * num_heads, bias=False)
        self.v = nn.Linear(embed_dim, value_dim * num_heads, bias=False)
        self.out = nn.Linear(value_dim * num_heads, embed_dim, bias=False)



    def forward(self, x: torch.Tensor) -> torch.Tensor:
        """Forward of multi-head self-attention

        Args:
            x (torch.Tensor): Input tensor of shape (B, D, H, W) (batch,␣
↪embedding dimension, height, width)

        Returns:
            torch.Tensor: Output tensor of shape (B, D, H, W) (batch, embedding␣
↪dimension, height, width)
        """
        B, D, H, W = x.shape
        # TODO: Student. Don't forget to implement scaling of the attention␣
↪logits by 1/sqrt(head_dim).
        # Implement a standard multi-head self-attention mechanism in a fully␣
↪batched manner (no explicit for loops etc, pure PyTorch/einops code)
        # The expected behavior of this method is that described in Eq. 2 of␣
↪Attention Is All You Need, Vaswani et al., 2017, NeurIPS.
        # In the case of single-head attention, the expected behavior is␣
↪described by Eq. 1 of the same paper
        # Hint when you run into problems:
        # For consistency with the multi-head reference implementation the unit␣
↪test compares against, make sure that the individual heads are arranged␣
↪correctly in q, k, v, and out.
        # The convention is that each head's part in q/k/v is contiguous, i.e.,
        # if you want to get the query for head 0, it's at q[..., :head_dim],␣
↪head 1 is at q[..., head_dim:2*head_dim], etc.

        # Flatten height and width to make x suitable for input layers
        x = einops.rearrange(x, 'b d h w -> b (h w) d')

        # Perform linear transformations
        q = self.q(x)
        k = self.k(x)
        v = self.v(x)

        # Split q, k, v into multiple heads
        q = einops.rearrange(q, 'b q_len (num_heads head_dim)  -> b q_len␣
↪num_heads head_dim ', num_heads=self.num_heads)
        k = einops.rearrange(k, 'b k_len (num_heads head_dim)  -> b k_len␣
↪num_heads head_dim ', num_heads=self.num_heads)
        v = einops.rearrange(v, 'b v_len (num_heads value_dim)  -> b v_len␣
↪num_heads value_dim ', num_heads=self.num_heads)

        # Calculate the attention scores

        # q shape: (b, q_len, num_heads, head_dim)
        # k shape: (b, k_len, num_heads, head_dim)
        energy = torch.einsum("bqhd,bkhd -> bhqk", [q, k])
        # energy shape: (b, num_heads, q_len, k_len)

        attention = torch.softmax(energy / (self.head_dim ** (0.5)) , dim=3) #␣
↪apply to key dimension => normalize the scores to sum up 1 one across the␣
↪source dimension key

        # attention shape: (b, num_heads, q_len, k_len)
        # v shape: (b, v_len, num_heads, heads_dim)
        out = torch.einsum('bhql,blhd -> bqhd', [attention, v]) # multiply␣
↪k_len and v_len dimensions together
        # out shape: (b, q_len, num_heads, head_dim)

        # concatenate num_heads head_dim into 1 dimension
        out = einops.rearrange(out, 'b q_len num_heads head_dim -> b q_len␣
↪(num_heads head_dim)')
        # out shape: (b, q_len, (num_heads head_dim) )

        out = self.out(out)
        # out shape: (b, q_len, (num_heads head_dim) )

        out = einops.rearrange(out, 'b (h w) d -> b d h w', h=H, w=W)

        return out

# Unit Test (single-head) DO NOT CHANGE!
with torch.no_grad():
    layer = SelfAttention2d(embed_dim=256, head_dim=256, value_dim=256,␣
↪num_heads=1).to(device)
    x = torch.randn((4, 256, 24, 24), device=device)
    res_layer = layer(x)

    layer_ref = nn.MultiheadAttention(layer.embed_dim, layer.num_heads).
↪to(device)
    layer_ref.load_state_dict({ 'in_proj_weight': torch.cat([layer.q.weight,␣
↪layer.k.weight, layer.v.weight]), 'out_proj.weight': layer.out.weight },␣
↪strict=False)
    res_ref = layer_ref(*[x.view(*x.shape[:2], -1).permute(2, 0, 1)] * 3)[0].
↪permute(1, 2, 0).view(*x.shape)
    assert torch.allclose(res_layer, res_ref, rtol=1e-2, atol=1e-5),␣
↪'Single-head attention result incorrect.'

# Unit Test (multi-head) DO NOT CHANGE!
with torch.no_grad():
    layer = SelfAttention2d().to(device)
    x = torch.randn((4, 256, 24, 24), device=device)
    res_layer = layer(x)

    layer_ref = nn.MultiheadAttention(layer.embed_dim, layer.num_heads).
↪to(device)
    layer_ref.load_state_dict({ 'in_proj_weight': torch.cat([layer.q.weight,␣
↪layer.k.weight, layer.v.weight]), 'out_proj.weight': layer.out.weight },␣
↪strict=False)
    res_ref = layer_ref(*[x.view(*x.shape[:2], -1).permute(2, 0, 1)] * 3)[0].
↪permute(1, 2, 0).view(*x.shape)
```

```
    assert torch.allclose(res_layer, res_ref, rtol=1e-2, atol=1e-5),␣
  ↪'Multi-head attention result incorrect.'

print('All tests passed.')
```

```
All tests passed.
```

vision_transformer

July 2, 2024

1 Exercise 11 Part 2: Vision Transformers

Summer Semester 2024

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1.0.1 Task: Implement & Train a ViT

Refer to the lecture and the original ViT paper (*AN IMAGE IS WORTH 16X16 WORDS: TRANSFORMERS FOR IMAGE RECOGNITION AT SCALE*, Dosovitskiy et al., 2020) for details. The naming of the hyperparameters is as in the aforementioned paper.

Similar to Part 1, you're expected to implement each block yourself, although you're allowed to use blocks like `torch.nn.MultiheadAttention`, `torch.nn.Linear`, etc. Implement the blocks as in the original ViT paper. No usage of things such as full pre-made FFN/self-attention blocks or full transformer implementations like `torchvision.models.vision_transformer.VisionTransformer` is allowed for this exercise. You're expected to do full vectorized implementations in native PyTorch (again, einops is allowed) without relying on Python for loops for things such as patching etc.

Some relevant details: - For simplicity of implementation, we will use a randomly (Gaussian with mean 0 and variance 1) initialized *learnable* positional embedding, not a Fourier/sinusoidal one. - Don't forget about all of the layer norms! - Consider the `batch_first` attribute of `nn.MultiheadAttention`, should you use that class - We'll make the standard assumption that $\dim_{\text{head}} = \dim_{\text{hidden}}/N_{\text{heads}}$

[ ]:
```python
import math

import torch
import torch.nn as nn
import torch.nn.functional as F
import torchvision.transforms as T
from torchvision.datasets import CIFAR10
from torch.utils.data import DataLoader
import matplotlib.pyplot as plt
from tqdm.auto import tqdm

# Optional
import einops
```

```
device = 'mps' if torch.backends.mps.is_available() else ('cuda' if torch.cuda.
 ↪is_available() else 'cpu')
print(f'Using device "{device}".')
```

```
Using device "cuda".
```

```
c:\Users\adria\anaconda3\envs\genai\Lib\site-packages\tqdm\auto.py:21:
TqdmWarning: IProgress not found. Please update jupyter and ipywidgets. See
https://ipywidgets.readthedocs.io/en/stable/user_install.html
  from .autonotebook import tqdm as notebook_tqdm
```

[ ]:
```
class ResidualModule(nn.Module):
    def __init__(
            self,
            inner_module: nn.Module
        ):
        super().__init__()
        self.inner_module = inner_module

    def forward(self, x: torch.Tensor) -> torch.Tensor:
        return x + self.inner_module(x)

class FeedForwardBlock(nn.Module):
    # TODO: Student (1P)
    # Tip: Dropout goes after each linear layer in the feedforward block
    def __init__(self, in_channel, hidden_channel, out_channel, p_dropout):
        super().__init__()

        self.fc1 = nn.Linear(in_channel, hidden_channel)
        self.dropout = nn.Dropout(p=p_dropout)
        self.activation = nn.GELU()
        self.fc2 = nn.Linear(hidden_channel, out_channel)

    def forward(self, x: torch.Tensor) -> torch.Tensor:
        out = self.fc1(x)
        out = self.dropout(out)
        out = self.activation(out)
        out = self.fc2(out)
        out = self.dropout(out)
        return out




class SelfAttentionTransformerBlock(nn.Module):
    # TODO: Student (2P)
    # Should contain one self-attention block and use a FeedForwardBlock␣
 ↪instance for the mlp
```

```
    def __init__(self, n_heads, p_dropout, mlp_size, hidden_size):
        super().__init__()

        self.norm1 = nn.LayerNorm(hidden_size)
        # set batch_first to true since we have the dimension: (batch_sizer,␣
↪seq_length, embedding_dim)
        self.attention = nn.MultiheadAttention(embed_dim=hidden_size,␣
↪num_heads=n_heads, batch_first=True)

        self.norm2 = nn.LayerNorm(hidden_size)
        self.mlp = FeedForwardBlock(in_channel=hidden_size,␣
↪hidden_channel=mlp_size, out_channel=hidden_size, p_dropout=p_dropout)


    def forward(self, x):
        # Attention part
        x_norm = self.norm1(x)
        attn_output, _ = self.attention(x_norm, x_norm, x_norm) # do not take␣
↪the weights
        x = x + attn_output

        # MLP part
        x_norm = self.norm2(x)
        out = self.mlp(x_norm)
        out = x + out

        return out



class VisionTransformer(nn.Module):
    def __init__(
            self,
            in_channels: int = 3,
            patch_size: int = 4,
            image_size: int = 32,
            layers: int = 6,
            hidden_size: int = 256,
            mlp_size: int = 512,
            n_heads: int = 8,
            num_classes: int = 10,
            p_dropout: float = 0.2,
        ):
        super().__init__()

        # TODO: Student (2P)
        self.patch_size = patch_size
        self.hidden_size = hidden_size
        self.num_patches = int(image_size / patch_size * image_size /␣
↪patch_size)
        self.token_length = int(self.patch_size ** 2 * in_channels)

        # For patch generation
        self.split = nn.Unfold(kernel_size=self.patch_size, stride=self.
↪patch_size, padding=0).to(device)
        self.project = nn.Linear(in_features=self.token_length,␣
↪out_features=self.hidden_size).to(device)
        # Draw from normal distribution with mean 0 variance 1
        self.positional_embeddings = nn.Parameter(torch.randn(self.
↪num_patches+1, self.hidden_size )).to(device) # +1 because of class_token

        # Initialize as many encoders as there should be layers
        self.encoders = nn.
↪ModuleList([SelfAttentionTransformerBlock(hidden_size=hidden_size,␣
↪n_heads=n_heads, p_dropout=p_dropout, mlp_size=mlp_size).to(device)
        for _ in range(layers)
        ])
        # Label prediction
        self.norm = nn.LayerNorm(hidden_size).to(device)
        self.classifier = nn.Linear(in_features=hidden_size,␣
↪out_features=num_classes).to(device)

    def patchify(self, x: torch.Tensor) -> torch.Tensor:
        """Takes an image tensor of shape (B, C, H, W) and transforms it to a␣
↪sequence of patches (B, L, D), with a learnable linear projection after␣
↪flattening,
        and a standard additive positional encoding applied. Note that the␣
↪activations in (Vision) Transformer implementations are
        typically passed around in channels-_last_ layout, different from␣
↪typical PyTorch norms.

        Args:
            x (torch.Tensor): Input tensor of shape (B, C, H, W)

        Returns:
            torch.Tensor: Embedded patch sequence tensor with positional␣
↪encodings applied and shape (B, L, D)
        """
        # TODO: Student (2P)
        B, C, H, W = x.shape

        # Calculate the number of tokens (L)
        assert(H % self.patch_size == 0), "The hight of the image is not␣
↪divisable by the path_size"
        assert(W % self.patch_size == 0), "The width of the image is not␣
↪divisable by the path_size"
        num_patches_check = H / self.patch_size * W / self.patch_size
        assert(self.num_patches == num_patches_check), "self.image_size does␣
↪not correlate with x dimensions"

        # Split the image tensor x into patches and pass through forward layer
        x_split = self.split(x)
        x_split = einops.rearrange(x_split, 'b d l -> b l d') # l = num␣
↪patches, d = patch_length
        tokens = self.project(x_split)

        # Prepend a class token to the tokens
        class_token = torch.zeros(1, 1, self.hidden_size).expand(B, -1, -1).
↪to(device)

        # Concatenate the class token with the tokens along the num token␣
↪dimension
        tokens = torch.cat((class_token, tokens), dim=1)

        # Add a position embedding for our tokens
        tokens += self.positional_embeddings

        return tokens

    def forward(self, x: torch.Tensor) -> torch.Tensor:
        """Takes an image tensor of shape (B, C, H, W), applies patching, a␣
↪standard ViT and then an output projection of the CLS token
        to finally create a class logit prediction of shape (B, N_cls)

        Args:
            x (torch.Tensor): Input tensor of shape (B, C, H, W)

        Returns:
            torch.Tensor: Output logits of shape (B, N_cls)
        """
        # TODO: Student (1P)
        x = x.to(device)
        tokens = self.patchify(x)

        for encoder in self.encoders:
            tokens = encoder(tokens)

        tokens = self.norm(tokens)
        class_token = tokens[:,0] # take the first token which corresponds to␣
↪the class token
        class_prediction = self.classifier(class_token)
        return class_prediction
```

1.0.2 Training

Do not modify this code! You are free to modify the four parameters in the first block, although no modifications should be necessary to achieve >70% validation accuracy with a correct transformer implementation.

[ ]:
```
DATASET_CACHE_DIR = './data'
BATCH_SIZE = 128
LR = 3e-4
N_EPOCHS = 50

import ssl
ssl._create_default_https_context = ssl._create_unverified_context # I had to␣
↪add this, or I would not have been possible to download the dataset
```

[ ]:
```
transforms_val = T.Compose([
    T.ToTensor(),
    T.Normalize([0.49139968, 0.48215841, 0.44653091], [0.24703223, 0.24348513,␣
↪0.26158784]),
])
transforms_train = T.Compose([
    T.RandomHorizontalFlip(),
    T.RandomResizedCrop((32, 32), scale=(0.8, 1.0), ratio=(0.9, 1.1)),
    T.ToTensor(),
    T.Normalize([0.49139968, 0.48215841, 0.44653091], [0.24703223, 0.24348513,␣
↪0.26158784]),
])

model = VisionTransformer().to(device)
optim = torch.optim.Adam(model.parameters(), lr=LR)
loss_fn = nn.CrossEntropyLoss()


dataloader_train = DataLoader(CIFAR10(root=DATASET_CACHE_DIR, train=True,␣
↪download=True, transform=transforms_train), batch_size=BATCH_SIZE,␣
↪shuffle=True, drop_last=True, num_workers=4)
dataloader_val = DataLoader(CIFAR10(root=DATASET_CACHE_DIR, train=False,␣
↪download=True, transform=transforms_val), batch_size=BATCH_SIZE,␣
↪shuffle=False, drop_last=False, num_workers=4)

train_losses = []
val_accs = []
```

```python
for i_epoch in range(N_EPOCHS):
    for i_step, (images, labels) in (pbar := tqdm(enumerate(dataloader_train),␣
 ↪desc=f'Training (Epoch {i_epoch + 1}/{N_EPOCHS})')):
        optim.zero_grad()
        loss = loss_fn(model(images.to(device)), labels.to(device))
        loss.backward()
        optim.step()

        # Some logging
        loss_val = loss.detach().item()
        train_losses.append(loss_val)
        pbar.set_postfix({ 'loss': loss_val } | ({ 'val_acc': val_accs[-1] } if␣
 ↪len(val_accs) > 0 else { }))

    # Validation every epoch
    with torch.no_grad():
        n_total, n_correct = 0, 0
        for i_step, (images, labels) in (pbar :=␣
 ↪tqdm(enumerate(dataloader_val), desc='Validating')):
            predicted = model(images.to(device)).argmax(dim=-1)
            n_correct += (predicted.cpu() == labels).float().sum().item()
            n_total += labels.shape[0]
        val_accs.append(n_correct / n_total)
        print(f'Validation accuracy: {val_accs[-1]:.3f}')

plt.figure(figsize=(6, 3))
plt.subplot(121)
plt.plot(train_losses)
plt.xlabel('Steps')
plt.ylabel('Training Loss')
plt.subplot(122)
plt.plot(val_accs)
plt.xlabel('Epochs')
plt.ylabel('Validation Accuracy')
plt.tight_layout()
plt.show()
```

```
Files already downloaded and verified
Files already downloaded and verified

Training (Epoch 1/50): 390it [00:28, 13.85it/s, loss=1.43]
Validating: 79it [00:02, 26.51it/s]

Validation accuracy: 0.503

Training (Epoch 2/50): 390it [00:28, 13.86it/s, loss=1.18, val_acc=0.503]
Validating: 79it [00:02, 27.02it/s]
```

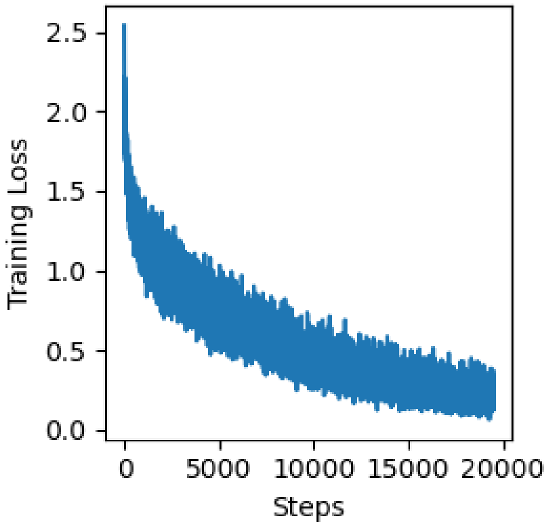
```
Validation accuracy: 0.557

Training (Epoch 3/50): 390it [00:27, 14.03it/s, loss=1.25, val_acc=0.557]
Validating: 79it [00:02, 27.03it/s]

Validation accuracy: 0.587

Training (Epoch 4/50): 390it [00:28, 13.63it/s, loss=1, val_acc=0.587]
Validating: 79it [00:02, 28.86it/s]

Validation accuracy: 0.609

Training (Epoch 5/50): 390it [00:29, 13.22it/s, loss=0.957, val_acc=0.609]
Validating: 79it [00:03, 25.84it/s]

Validation accuracy: 0.627

Training (Epoch 6/50): 390it [00:28, 13.47it/s, loss=0.935, val_acc=0.627]
Validating: 79it [00:03, 26.14it/s]

Validation accuracy: 0.635

Training (Epoch 7/50): 390it [00:28, 13.53it/s, loss=0.803, val_acc=0.635]
Validating: 79it [00:03, 25.39it/s]

Validation accuracy: 0.637

Training (Epoch 8/50): 390it [00:28, 13.60it/s, loss=0.89, val_acc=0.637]
Validating: 79it [00:02, 27.83it/s]

Validation accuracy: 0.655

Training (Epoch 9/50): 390it [00:28, 13.72it/s, loss=0.889, val_acc=0.655]
Validating: 79it [00:02, 27.37it/s]

Validation accuracy: 0.661

Training (Epoch 10/50): 390it [00:27, 14.09it/s, loss=0.898, val_acc=0.661]
Validating: 79it [00:02, 26.48it/s]

Validation accuracy: 0.671

Training (Epoch 11/50): 390it [00:28, 13.81it/s, loss=0.885, val_acc=0.671]
Validating: 79it [00:02, 27.59it/s]

Validation accuracy: 0.683

Training (Epoch 12/50): 390it [00:27, 14.00it/s, loss=0.747, val_acc=0.683]
Validating: 79it [00:02, 26.75it/s]

Validation accuracy: 0.687

Training (Epoch 13/50): 390it [00:28, 13.86it/s, loss=0.75, val_acc=0.687]
Validating: 79it [00:02, 26.97it/s]

Validation accuracy: 0.691

Training (Epoch 14/50): 390it [00:27, 14.06it/s, loss=0.659, val_acc=0.691]
Validating: 79it [00:02, 27.24it/s]
```

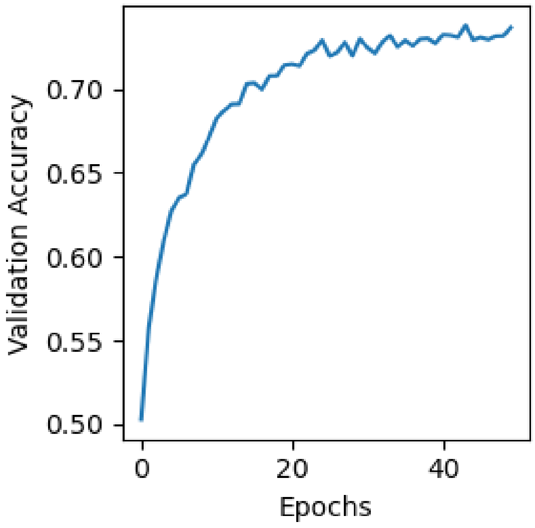
```
Validation accuracy: 0.691

Training (Epoch 15/50): 390it [00:27, 14.10it/s, loss=0.625, val_acc=0.691]
Validating: 79it [00:02, 27.14it/s]

Validation accuracy: 0.703

Training (Epoch 16/50): 390it [00:26, 14.85it/s, loss=0.583, val_acc=0.703]
Validating: 79it [00:02, 28.84it/s]

Validation accuracy: 0.704

Training (Epoch 17/50): 390it [00:26, 14.73it/s, loss=0.749, val_acc=0.704]
Validating: 79it [00:02, 29.35it/s]

Validation accuracy: 0.700

Training (Epoch 18/50): 390it [00:26, 14.79it/s, loss=0.835, val_acc=0.7]
Validating: 79it [00:02, 29.31it/s]

Validation accuracy: 0.708

Training (Epoch 19/50): 390it [00:26, 14.70it/s, loss=0.523, val_acc=0.708]
Validating: 79it [00:02, 28.92it/s]

Validation accuracy: 0.708

Training (Epoch 20/50): 390it [00:26, 14.57it/s, loss=0.548, val_acc=0.708]
Validating: 79it [00:02, 28.12it/s]

Validation accuracy: 0.714

Training (Epoch 21/50): 390it [00:26, 14.61it/s, loss=0.576, val_acc=0.714]
Validating: 79it [00:02, 28.78it/s]

Validation accuracy: 0.715

Training (Epoch 22/50): 390it [00:26, 14.87it/s, loss=0.567, val_acc=0.715]
Validating: 79it [00:02, 28.50it/s]

Validation accuracy: 0.714

Training (Epoch 23/50): 390it [00:26, 14.84it/s, loss=0.515, val_acc=0.714]
Validating: 79it [00:02, 28.40it/s]

Validation accuracy: 0.721

Training (Epoch 24/50): 390it [00:26, 14.73it/s, loss=0.714, val_acc=0.721]
Validating: 79it [00:03, 24.64it/s]

Validation accuracy: 0.723

Training (Epoch 25/50): 390it [00:26, 14.47it/s, loss=0.462, val_acc=0.723]
Validating: 79it [00:02, 28.63it/s]

Validation accuracy: 0.729

Training (Epoch 26/50): 390it [00:26, 14.89it/s, loss=0.571, val_acc=0.729]
Validating: 79it [00:02, 29.69it/s]
```

```
Validation accuracy: 0.720

Training (Epoch 27/50): 390it [00:26, 14.84it/s, loss=0.531, val_acc=0.72]
Validating: 79it [00:02, 28.63it/s]

Validation accuracy: 0.722

Training (Epoch 28/50): 390it [00:26, 14.86it/s, loss=0.526, val_acc=0.722]
Validating: 79it [00:02, 29.82it/s]

Validation accuracy: 0.728

Training (Epoch 29/50): 390it [00:26, 14.85it/s, loss=0.6, val_acc=0.728]
Validating: 79it [00:02, 29.35it/s]

Validation accuracy: 0.720

Training (Epoch 30/50): 390it [00:26, 14.75it/s, loss=0.538, val_acc=0.72]
Validating: 79it [00:02, 29.44it/s]

Validation accuracy: 0.730

Training (Epoch 31/50): 390it [00:26, 14.88it/s, loss=0.416, val_acc=0.73]
Validating: 79it [00:02, 29.43it/s]

Validation accuracy: 0.725

Training (Epoch 32/50): 390it [00:26, 14.86it/s, loss=0.39, val_acc=0.725]
Validating: 79it [00:02, 28.94it/s]

Validation accuracy: 0.721

Training (Epoch 33/50): 390it [00:26, 14.74it/s, loss=0.344, val_acc=0.721]
Validating: 79it [00:02, 29.77it/s]

Validation accuracy: 0.728

Training (Epoch 34/50): 390it [00:26, 14.91it/s, loss=0.414, val_acc=0.728]
Validating: 79it [00:02, 28.75it/s]

Validation accuracy: 0.732

Training (Epoch 35/50): 390it [00:26, 14.93it/s, loss=0.317, val_acc=0.732]
Validating: 79it [00:02, 29.73it/s]

Validation accuracy: 0.725

Training (Epoch 36/50): 390it [00:26, 14.94it/s, loss=0.346, val_acc=0.725]
Validating: 79it [00:02, 30.66it/s]

Validation accuracy: 0.729

Training (Epoch 37/50): 390it [00:26, 14.92it/s, loss=0.315, val_acc=0.729]
Validating: 79it [00:02, 30.37it/s]

Validation accuracy: 0.726

Training (Epoch 38/50): 390it [00:27, 14.00it/s, loss=0.31, val_acc=0.726]
Validating: 79it [00:02, 29.17it/s]
```

```
Validation accuracy: 0.730

Training (Epoch 39/50): 390it [00:27, 13.98it/s, loss=0.438, val_acc=0.73]
Validating: 79it [00:02, 27.86it/s]

Validation accuracy: 0.730

Training (Epoch 40/50): 390it [00:28, 13.58it/s, loss=0.342, val_acc=0.73]
Validating: 79it [00:02, 26.59it/s]

Validation accuracy: 0.727

Training (Epoch 41/50): 390it [00:27, 14.00it/s, loss=0.21, val_acc=0.727]
Validating: 79it [00:02, 27.73it/s]

Validation accuracy: 0.732

Training (Epoch 42/50): 390it [00:28, 13.81it/s, loss=0.359, val_acc=0.732]
Validating: 79it [00:02, 27.78it/s]

Validation accuracy: 0.732

Training (Epoch 43/50): 390it [00:27, 13.99it/s, loss=0.203, val_acc=0.732]
Validating: 79it [00:02, 27.02it/s]

Validation accuracy: 0.731

Training (Epoch 44/50): 390it [00:27, 14.03it/s, loss=0.35, val_acc=0.731]
Validating: 79it [00:02, 27.78it/s]

Validation accuracy: 0.738

Training (Epoch 45/50): 390it [00:27, 14.09it/s, loss=0.229, val_acc=0.738]
Validating: 79it [00:03, 26.07it/s]

Validation accuracy: 0.729

Training (Epoch 46/50): 390it [00:28, 13.83it/s, loss=0.256, val_acc=0.729]
Validating: 79it [00:02, 27.21it/s]

Validation accuracy: 0.731

Training (Epoch 47/50): 390it [00:28, 13.61it/s, loss=0.215, val_acc=0.731]
Validating: 79it [00:02, 26.87it/s]

Validation accuracy: 0.730

Training (Epoch 48/50): 390it [00:28, 13.71it/s, loss=0.216, val_acc=0.73]
Validating: 79it [00:02, 26.97it/s]

Validation accuracy: 0.732

Training (Epoch 49/50): 390it [00:27, 14.10it/s, loss=0.138, val_acc=0.732]
Validating: 79it [00:02, 27.10it/s]

Validation accuracy: 0.732

Training (Epoch 50/50): 390it [00:27, 14.07it/s, loss=0.233, val_acc=0.732]
Validating: 79it [00:02, 28.02it/s]
```

```
Validation accuracy: 0.737
```


Training Loss
Steps


Validation Accuracy
Epochs