CIFAR-10 Image Classification Using Residual Network (ResNet)Architecture

Andrea Zhou(az2482), Elisha Edme(eae8374), Abdul Samad Zaheer Khan(ak9943)
New York University

Links to Supporting Material
GitHub Repository: GitHub (For the best results use learn_rate_consistent_model.pth in the model folder)

Abstract

The CIFAR-10 dataset serves as a benchmark for image classification tasks in the domains of machine learning and computer vision. The ResNet9 model is a compact version of ResNet-18, designed with a reduced number of trainable parameters to meet specific constraints. ResNet9 is defined as ResNet(BasicBlock, [1, 1, 1, 1]) and incorporates a single BasicBlock in each layer. Multiple iterations of hyperparameter tuning were meticulously conducted to optimize the model's performance. These tuning processes involved experimenting with various combinations of optimizers, learning rates, momentum, and weight decay. After thorough evaluation, the optimal set of hyperparameters was identified, resulting in an impressive training accuracy of 97% and a testing accuracy of 92%. The model was trained over 100 epochs to achieve the current levels of accuracy.

Overview

Deep neural networks, characterized by their multiple hidden layers, have proven remarkably effective in various tasks such as image recognition and natural language processing. However, constructing deeper networks often encounters a degradation issue, wherein the training error unexpectedly increases despite an increase in network capacity. Additionally, the vanishing gradient descent problem arises, where gradients diminish significantly during backpropagation, impeding learning in deeper layers. These challenges collectively limit the performance and practical applications of deep networks.

ResNet, a groundbreaking architecture that incorporates residual connections, has emerged as a promising solution to these challenges. By addressing the degradation problem and enabling more efficient training of deep networks, ResNet offers significant advantages in various domains. The effectiveness of ResNet lies in its ability to alleviate the vanishing gradient descent problem and facilitate the flow of information across layers, thereby improving the overall performance of deep neural networks.

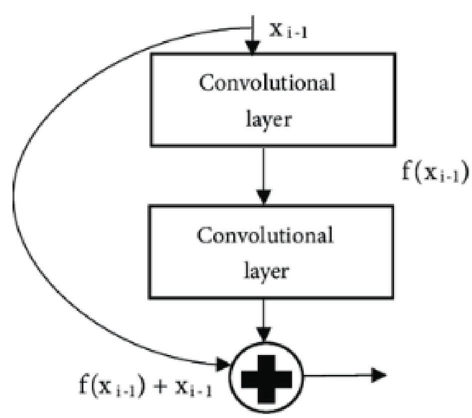


Fig. 1

ResNet's contributions to deep learning have been transformative, solidifying its status as a foundational architecture for computer vision tasks. Its innovative approach to addressing training challenges in deep networks has inspired a plethora of variants and extensions, collectively driving the field forward. The insights gleaned from ResNet have had a profound impact on the design and training methodologies of contemporary deep neural networks, facilitating their successful application across a diverse range of tasks and domains.

Data Augmentation

Data augmentation is a technique in deep learning that expands the training set by applying transformations to existing data. This includes rotations, scaling, and flipping. Augmentation enhances performance and generalization by exposing the network to a diverse set of examples. It reduces overfitting and improves the handling of data variations. It's commonly used in computer vision to boost deep neural network performance. Data augmentation techniques implemented for the current ResNet9 model are as follows:

Random Crop with Padding:

Images were augmented by adding pixels with a given width, and then the padded images were cropped to the appropriate size. The current implementation, 4 pixels were added to each 32x32 image to get a 40x40 padded image. After random cropping, the final 32x32 image is ready for training.

Normalize:

First, convert the image to a tensor using ToTensor() and then normalize the tensor image with mean and standard deviation.

Random Horizontal Flip:

This transformation randomly flips the images horizontally, creating new images with mirrored versions of the original images.

Random Rotation:

This transformation randomly rotates the images by a random angle. The current implementation randomly rotates the image between -10 and 10 degrees, augmenting the dataset with images captured from different perspectives.

About the CIFAR-10 Dataset

CIFAR-10 is a benchmark dataset used for image classification tasks in the field of machine learning and computer vision. It consists of 60,000 32x32 color images in 10 classes, with 6,000 images per class. The 10 classes are airplane, automobile, bird, cat, deer, dog, frog, horse, ship, and truck.

The dataset is split into 50,000 training images and 10,000 test images. It is often used as a standard benchmark to evaluate the performance of image classification algorithms, and many state-of-the-art models have been trained on this dataset.

The name "CIFAR" stands for Canadian Institute for Advanced Research, which is the organization that created the dataset.

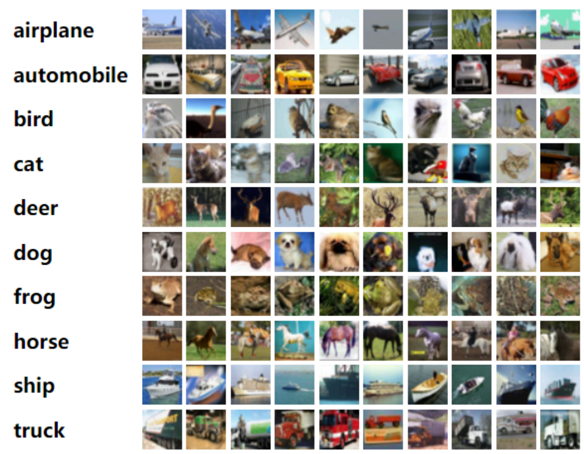


Fig. 2

Architecture

The number of basic blocks per convolutional layer was from two to just one BasicBlock in all the layers of the model, resulting in the architecture shown in Fig. 3. After this we decided to remove one residual layer from the above architecture. Also, one residual layer was removed from the architecture.

The model will consist of a preprocessing convolution layer with 64 output channels, one residual network, and one fully connected layer.

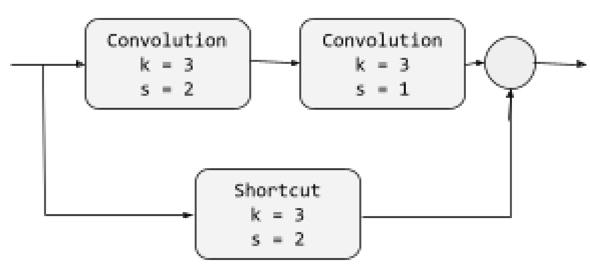


Fig. 3

Methodology

Starting with the ResNet18 architecture, our main objective was to reduce the number of trainable parameters to fulfill the 5 million parameter limit. This is done by implementing the architecture explained in the previous section. This section outlines the methodology employed for implementing the ResNet9 model for image classification on the CIFAR-10 dataset.

Data Preprocessing:

We started by downloading the CIFAR-10 dataset and subjecting it to preprocessing to ensure uniformity and compatibility with the model. To enhance the model's robustness and augment the training set, we applied data augmentation techniques, including random flipping, random rotation, and random cropping with padding. Then we normalized the images and converted them into tensors.

Model Architecture:

The ResNet9 model was constructed by leveraging the fundamental principles of the ResNet architecture, specifically utilizing the BasicBlock building block. The model comprises a preprocessing convolutional layer with 64 output channels, followed by a residual network consisting of a single residual layer, culminating in a fully connected layer

Training:

The model underwent rigorous training using the Stochastic Gradient Descent (SGD) optimizer, with a carefully chosen learning rate of 0.01 and a momentum of 0.9. To measure the discrepancy between the predicted and actual labels, we employed the cross-entropy loss function.

The model was diligently trained for 100 epochs, ensuring its optimal performance, with the batch size judiciously set to 64.

A custom function was implemented to calculate the accuracy of the model in the no_labels_dataset. Every epoch if the accuracy exceeded the previous best accuracy then the model was saved and reloaded before the next iteration to avoid a significant reduction in accuracy in the following iteration.

Evaluation:

To ascertain the efficacy of the trained model, we conducted a thorough evaluation of the CIFAR-10 test set, assessing its accuracy.

The model demonstrated acceptable performance, achieving a training accuracy of 97% and a testing accuracy of 92%, showcasing its proficiency in classifying images.

The train loss and test loss over 60 epochs are plotted in Fig. 4.

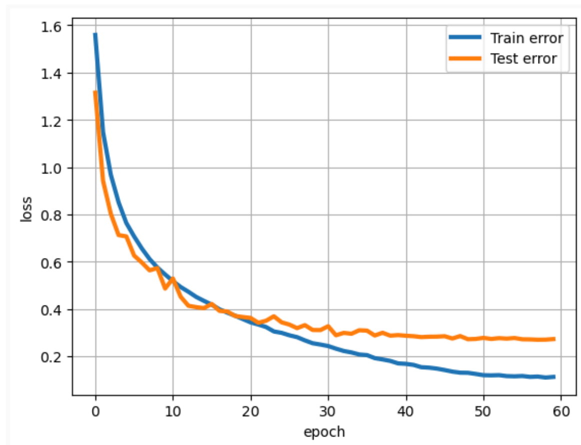


Fig. 4

The train accuracy and test accuracy of the model on the first 60 iterations of the more than 100 epochs of the model is plotted in Fig. 5.

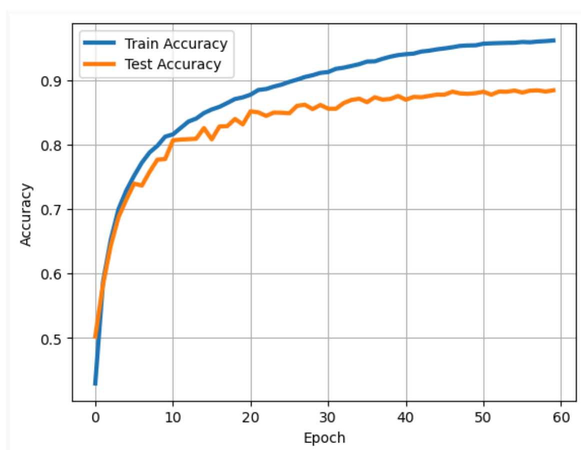


Fig. 5

Implementation Details:

The basic structure of the model was modified to meet the parameter constraints. The model was implemented with assistance from the PyTorch deep learning library, harnessing its capabilities for efficient and effective deep learning development.

Results

Performance:

- Test accuracy: 92%

Number of Parameters: 4903242

Improvements

The attempted pruning and fine-tuning of the model failed as the accuracy significantly plummeted after the pruning of parameters. Pruning could work in case of more training or proper implementation using deeper models.

Possible improvements using different architectures like Teacher-Student Architecture for Knowledge Distillation which might not meet the trainable parameters constraint. The model can also be improved using better Data Augmentation Techniques, trying Deeper or Wider Neural Networks, experimenting with Different Activation Functions like ELU, etc.

References

1. Deep Residual Learning for Image Recognition, 2016. Kaiming He, Xiangyu Zhang, Shaoqing Ren, Jian Sun.
2. "Deep Learning with Python" by Francois Chollet
3. "The Elements of Statistical Learning" by Trevor Hastie, Robert Tibshirani, and Jerome Friedman.
4. "Data Augmentation for Deep Learning" by Jason Brownlee
5. Teacher-Student Architecture for Knowledge Distillation: A Survey, 2023. Chengming Hu, Xuan Li, Dan Liu, Haolun Wu, Xi Chen, Ju Wang, Xue Liu
6. https://github.com/kuangliu/pytorch-cifar
7. https://openreview.net/forum?id=SeFiP8YAJy
8. https://www.researchgate.net/publication/352772872_Improvement_of_CIFAR-10_Image_Classification_Based_on_Modified_ResNet-34

In [2]:
```
'''ResNet in PyTorch.

For Pre-activation ResNet, see 'preact_resnet.py'.

Reference:
[1] Kaiming He, Xiangyu Zhang, Shaoqing Ren, Jian Sun
    Deep Residual Learning for Image Recognition. arXiv:1512.03385
'''
import torch
import torch.nn as nn
import torch.nn.functional as F
```

In [3]:
```
class BasicBlock(nn.Module):
    expansion = 1

    def __init__(self, in_planes, planes, stride=1, prob_dropout=0.3):
        super(BasicBlock, self).__init__()
        self.conv1 = nn.Conv2d(
            in_planes, planes, kernel_size=3, stride=stride, padding=1, bias
        self.bn1 = nn.BatchNorm2d(planes)

        # mod here
        self.dropout1 = nn.Dropout2d(p=prob_dropout)

        self.conv2 = nn.Conv2d(planes, planes, kernel_size=3,
                               stride=1, padding=1, bias=False)
        self.bn2 = nn.BatchNorm2d(planes)


        # mod here
        self.dropout2 = nn.Dropout2d(p=prob_dropout)

        self.shortcut = nn.Sequential()
        if stride != 1 or in_planes != self.expansion*planes:
            self.shortcut = nn.Sequential(
                nn.Conv2d(in_planes, self.expansion*planes,
                          kernel_size=1, stride=stride, bias=False),
                nn.BatchNorm2d(self.expansion*planes)
            )

    def forward(self, x):

        out = F.relu(self.bn1(self.conv1(x)))
        out = self.bn2(self.conv2(out))
        out += self.shortcut(x)
        out = F.relu(out)
        return out
```

In [4]:
```
class Bottleneck(nn.Module):
    expansion = 4

    def __init__(self, in_planes, planes, stride=1):
        super(Bottleneck, self).__init__()
        self.conv1 = nn.Conv2d(in_planes, planes, kernel_size=1, bias=False)
```

```
        self.bn1 = nn.BatchNorm2d(planes)
        self.conv2 = nn.Conv2d(planes, planes, kernel_size=3,
                               stride=stride, padding=1, bias=False)
        self.bn2 = nn.BatchNorm2d(planes)
        self.conv3 = nn.Conv2d(planes, self.expansion *
                               planes, kernel_size=1, bias=False)
        self.bn3 = nn.BatchNorm2d(self.expansion*planes)

        self.shortcut = nn.Sequential()
        if stride != 1 or in_planes != self.expansion*planes:
            self.shortcut = nn.Sequential(
                nn.Conv2d(in_planes, self.expansion*planes,
                          kernel_size=1, stride=stride, bias=False),
                nn.BatchNorm2d(self.expansion*planes)
            )

    def forward(self, x):
        out = F.relu(self.bn1(self.conv1(x)))
        out = F.relu(self.bn2(self.conv2(out)))
        out = self.bn3(self.conv3(out))
        out += self.shortcut(x)
        out = F.relu(out)
        return out
```

In [5]:
```
class ResNet(nn.Module):
    def __init__(self, block, num_blocks, num_classes=10):
        super(ResNet, self).__init__()
        self.in_planes = 64

        self.conv1 = nn.Conv2d(3, 64, kernel_size=3,
                               stride=1, padding=1, bias=False)
        self.bn1 = nn.BatchNorm2d(64)
        self.layer1 = self._make_layer(block, 64, num_blocks[0], stride=1)
        self.layer2 = self._make_layer(block, 128, num_blocks[1], stride=2)
        self.layer3 = self._make_layer(block, 256, num_blocks[2], stride=2)
        self.layer4 = self._make_layer(block, 512, num_blocks[3], stride=2)
        self.linear = nn.Linear(512*block.expansion, num_classes)

    def _make_layer(self, block, planes, num_blocks, stride):
        strides = [stride] + [1]*(num_blocks-1)
        layers = []
        for stride in strides:
            layers.append(block(self.in_planes, planes, stride))
            self.in_planes = planes * block.expansion
        return nn.Sequential(*layers)

    def forward(self, x):
        out = F.relu(self.bn1(self.conv1(x)))
        out = self.layer1(out)
        out = self.layer2(out)
        out = self.layer3(out)
        out = self.layer4(out)
        out = F.avg_pool2d(out, 4)
        out = out.view(out.size(0), -1)
```

```
        out = self.linear(out)
        return out
```

In [6]:
```
def ResNet9():
    return ResNet(BasicBlock, [1, 1, 1, 1])

def ResNet18():
    return ResNet(BasicBlock, [2, 2, 2, 2])


# def ResNet34():
#     return ResNet(BasicBlock, [3, 4, 6, 3])


# def ResNet50():
#     return ResNet(Bottleneck, [3, 4, 6, 3])


# def ResNet101():
#     return ResNet(Bottleneck, [3, 4, 23, 3])


# def ResNet152():
#     return ResNet(Bottleneck, [3, 8, 36, 3])


# def test():
#     net = ResNet18()
#     y = net(torch.randn(1, 3, 32, 32))
#     print(y.size())

# test()

print("done")
```

```
done
```

In [7]:
```
from torchvision import transforms, datasets
import torch.utils.data
from torchvision.transforms import ToTensor
```

In [8]:
```
torch.manual_seed(1024)
# Define transformations to be applied on the training dataset
train_transform = transforms.Compose([
    transforms.ColorJitter(brightness=0.1, contrast=0.1, saturation=0.1, hue
    transforms.RandomHorizontalFlip(), #apply horizontal flipping
    transforms.RandomCrop(32, padding=4),
    transforms.RandomHorizontalFlip(), # Randomly flip the images on the hor
    transforms.RandomRotation(10), # Randomly rotate the images by +/- 10 de
    transforms.RandomCrop(32, padding=4), # Apply random crops
    transforms.ToTensor(), # Convert images to PyTorch tensors
    transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5)), # Normalize imag
])

# Define transformations to be applied on the testing dataset
test_transform = transforms.Compose([
```

```
    transforms.ToTensor(),
    transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5)),
])

# Import the datasets and transform it
train_dataset = datasets.CIFAR10(root='./data', train=True, download=True, t
test_dataset = datasets.CIFAR10(root='./data', train=False, download=True, t

# Define the batch size for training
batch_size = 16

# Create DataLoader
trainDataLoader = torch.utils.data.DataLoader(train_dataset, batch_size=batc
testDataLoader = torch.utils.data.DataLoader(test_dataset, batch_size=batch_

# for batch in train_loader:
#     print(batch)
print("done")
```

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

In [9]:

```
# Import all the necessary libraries

import torch
import torchvision
import torchvision.transforms as transforms
import torch.nn as nn
import torch.optim as optim
import numpy as np
import pickle
from PIL import Image
import matplotlib.pyplot as plt

# Set a manual seed for reproducibility
torch.manual_seed(1024)
```

Out[9]:

```
<torch._C.Generator at 0x14f8511f2cd0>
```

In [10]:

```
# Function used to calculate the accuracy on the cifar_no_labels dataset
def calculate_accuracy(predictions):
    actual = []
    pattern = [8, 2, 9, 0, 4, 3, 6, 1, 7, 5]
    for num in pattern:
        actual.extend([num] * 1000)
    num_matches = sum(1 for pred, act in zip(predictions, actual) if pred ==
    accuracy = (num_matches / len(predictions)) * 100
    return accuracy
```

In [11]:

```
# Function to load and transform the cifar_no_labels dataset
def load_kaggle_data(file, transform=None):
    import pickle
    with open(file, 'rb') as fo:
        batch = pickle.load(fo, encoding='bytes')
    images = batch[b'data']
```

```
    images = images.reshape((-1, 3, 32, 32)).transpose(0, 2, 3, 1)
    min_val = np.min(images)
    max_val = np.max(images)
    images = (images - min_val) / (max_val - min_val) #normalizing facepalm
    processed_images=[]
    for i,image in enumerate(images):
        pil_image = Image.fromarray((image * 255).astype(np.uint8))
        # Apply transformation
        pil_image = transform(pil_image)

        # Append transformed image
        processed_images.append(pil_image)
    return processed_images
```

In [12]:

```
# Tranformation to be applied on the cifar_test_nolabels.pkl dataset
kaggle_transform = transforms.Compose([
    transforms.ToTensor(),
    transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))
])

# Loading the cifar_test_nolabels images and transforming as needed
test_images = load_kaggle_data('kaggle/cifar_test_nolabels.pkl', transform=k
kaggleLoader = torch.utils.data.DataLoader(test_images, batch_size=1,shuffle
print(len(kaggleLoader))
```

```
10000
```

In [13]:

```
import torch.optim.lr_scheduler as lr_scheduler

# Initialize empty lists to store training and test loss history
train_loss_history = []
test_loss_history = []
train_accuracy_history = []
test_accuracy_history = []

no_label_accuracy_history = []

# Initialize variables to track accuracy
matches = 0
total = 0

# Initialize the best Kaggle accuracy and learning rate
best_kagg_acc = 0.0
lr_best = -1

# Define a list of learning rates to try (commented out for now)
# lr_arr = [.003, .005, 0.0001, 0.0005, 0.0002, 0.0003, 0.0004, 0.005, 0.008

# Iterate through the learning rates (commented out for now)
# for learn_rate in lr_arr[:2]:

# Set the learning rate (using a fixed value for now)
learn_rate = .004
```

In [14]:

```
# Set the number of training epochs
```

```
num_epochs = 60
```

In [15]:

```
# Initialize model, loss function, optimizer, and learning rate scheduler
model = ResNet9().cuda() # .cuda to train on the GPU
loss = torch.nn.CrossEntropyLoss()
optimizer = torch.optim.SGD(model.parameters(), lr=learn_rate, momentum=0.9,
scheduler = lr_scheduler.CosineAnnealingLR(optimizer, T_max=num_epochs)  # T
```

In [16]:

```
# Print a message to indicate the start of the training loop
print("Beginning training arc now!~~~ \n")

for epoch in range(num_epochs):
    train_loss = 0.0
    test_loss = 0.0
    train_acc = 0.0
    test_acc = 0.0

    model.train()
    for i, data in enumerate(trainDataLoader):
        images, labels = data
        images = images.cuda()
        labels = labels.cuda()
        optimizer.zero_grad() # zero out any gradient values from the previo
        predicted_output = model(images) # forward propagation
        fit = loss(predicted_output, labels)  # calculate our measure of goo
        fit.backward() # backpropagation
        optimizer.step() # update the weights of our trainable parameters
        train_loss += fit.item()
        _, predicted = torch.max(predicted_output.data, 1)
        train_acc += (predicted == labels).sum().item()

    scheduler.step()
    for i, data in  enumerate(testDataLoader):
        with torch.no_grad():
            images, labels = data
            images = images.cuda()
            labels = labels.cuda()
            predicted_output = model(images)
            fit = loss(predicted_output, labels)
            test_loss += fit.item()
            _, predicted = torch.max(predicted_output.data, 1)
            matches += (predicted == labels).sum().item()
            total += labels.size(0)
            test_acc += (predicted == labels).sum().item()
    train_loss = train_loss / len(trainDataLoader)
    test_loss = test_loss / len(testDataLoader)
    train_acc = train_acc / len(trainDataLoader.dataset)
    test_acc = test_acc / len(testDataLoader.dataset)
    train_loss_history += [train_loss]
    test_loss_history += [test_loss]
    train_accuracy_history += [train_acc]
    test_accuracy_history += [test_acc]

    predictions = []
    # model.eval()
```

```
    # Saving the best model if it exceeds the previous best accuracy
    for image in kaggleLoader:
        image = image.cuda()
        with torch.no_grad():
            output = model(image)
        predictions.append(output.argmax().item())
    curr_acc = calculate_accuracy(predictions)
    if curr_acc > best_kagg_acc:
        best_kagg_acc = curr_acc
        torch.save(model.state_dict(), 'best_resnet9_model.pth')
    no_label_accuracy_history += [curr_acc]

    print(f'Epoch {epoch}, Train loss {train_loss}, Train accuracy {train_ac
```

```
Beginning training arc now!~~~

Epoch 0, Train loss 1.565065152053833, Train accuracy 0.429, Test loss 1.409
7601428985596, Test accuracy 0.502, NoLabel Accuracy 17.11
Epoch 1, Train loss 1.1578211816215516, Train accuracy 0.58694, Test loss 1.
187808895111084, Test accuracy 0.5829, NoLabel Accuracy 28.83
Epoch 2, Train loss 0.9826439865589142, Train accuracy 0.6525, Test loss 1.0
514758522987366, Test accuracy 0.6435, NoLabel Accuracy 22.509999999999998
Epoch 3, Train loss 0.8553131859731674, Train accuracy 0.70014, Test loss 0.
9139261562108993, Test accuracy 0.6875, NoLabel Accuracy 35.06
Epoch 4, Train loss 0.7726250850772858, Train accuracy 0.72884, Test loss 0.
8589714540958404, Test accuracy 0.7147, NoLabel Accuracy 36.25
Epoch 5, Train loss 0.7130328175830841, Train accuracy 0.75164, Test loss 0.
7514945923805236, Test accuracy 0.7394, NoLabel Accuracy 38.76
Epoch 6, Train loss 0.6559436442351341, Train accuracy 0.77198, Test loss 0.
7745088212013245, Test accuracy 0.7364, NoLabel Accuracy 37.980000000000004
Epoch 7, Train loss 0.6150526032543182, Train accuracy 0.7879, Test loss 0.7
079473152637482, Test accuracy 0.7578, NoLabel Accuracy 40.71
Epoch 8, Train loss 0.5791047469520569, Train accuracy 0.79818, Test loss 0.
6445163821697235, Test accuracy 0.7767, NoLabel Accuracy 45.45
Epoch 9, Train loss 0.5449702680659294, Train accuracy 0.81236, Test loss 0.
6579202128052711, Test accuracy 0.7776, NoLabel Accuracy 40.75
Epoch 10, Train loss 0.5274680589437485, Train accuracy 0.8159, Test loss 0.
5718300176024437, Test accuracy 0.8066, NoLabel Accuracy 45.69
Epoch 11, Train loss 0.4985662501525879, Train accuracy 0.82592, Test loss
0.5657376887559891, Test accuracy 0.8079, NoLabel Accuracy 48.87000000000000
5
Epoch 12, Train loss 0.47443469311118125, Train accuracy 0.83582, Test loss
0.5632015392065048, Test accuracy 0.8084, NoLabel Accuracy 46.6
Epoch 13, Train loss 0.45703014152288435, Train accuracy 0.84052, Test loss
0.5654279923379422, Test accuracy 0.8092, NoLabel Accuracy 48.85
Epoch 14, Train loss 0.4362173969078064, Train accuracy 0.8491, Test loss 0.
5220353974461556, Test accuracy 0.8257, NoLabel Accuracy 50.44
Epoch 15, Train loss 0.4160895113795996, Train accuracy 0.8546, Test loss 0.
5670471617817878, Test accuracy 0.8082, NoLabel Accuracy 49.09
Epoch 16, Train loss 0.40798100676357746, Train accuracy 0.8587, Test loss
0.5184087174713612, Test accuracy 0.8282, NoLabel Accuracy 50.32
Epoch 17, Train loss 0.38880334553897383, Train accuracy 0.86464, Test loss
0.5005707773327828, Test accuracy 0.8287, NoLabel Accuracy 47.21
Epoch 18, Train loss 0.3745120352858305, Train accuracy 0.87084, Test loss
0.4803273251593113, Test accuracy 0.8398, NoLabel Accuracy 48.94
Epoch 19, Train loss 0.36028610295176505, Train accuracy 0.87342, Test loss
0.507972255641222, Test accuracy 0.8315, NoLabel Accuracy 49.76
Epoch 20, Train loss 0.3497142912572622, Train accuracy 0.87758, Test loss
0.4499871678709984, Test accuracy 0.8517, NoLabel Accuracy 53.68000000000001
Epoch 21, Train loss 0.3335770726078749, Train accuracy 0.88486, Test loss
0.45198090255856516, Test accuracy 0.8501, NoLabel Accuracy 53.21
Epoch 22, Train loss 0.322429395595789, Train accuracy 0.88634, Test loss 0.
45899347985386846, Test accuracy 0.8446, NoLabel Accuracy 54.0
Epoch 23, Train loss 0.31269431653410196, Train accuracy 0.89018, Test loss
0.4456697785943747, Test accuracy 0.8498, NoLabel Accuracy 52.64
Epoch 24, Train loss 0.3030749848395586, Train accuracy 0.89318, Test loss
0.4614305145442486, Test accuracy 0.8495, NoLabel Accuracy 52.96999999999999
Epoch 25, Train loss 0.29022502734482286, Train accuracy 0.8975, Test loss
0.4573403076648712, Test accuracy 0.8487, NoLabel Accuracy 52.45999999999999
4
```

```
Epoch 26, Train loss 0.283657560082674, Train accuracy 0.901, Test loss 0.42
907574498951434, Test accuracy 0.8603, NoLabel Accuracy 55.44
Epoch 27, Train loss 0.2726796293652058, Train accuracy 0.90508, Test loss
0.4192110553309321, Test accuracy 0.8619, NoLabel Accuracy 55.769999999999
6
Epoch 28, Train loss 0.2641718540802598, Train accuracy 0.90782, Test loss
0.44235115008056164, Test accuracy 0.8552, NoLabel Accuracy 53.3399999999999
96
Epoch 29, Train loss 0.24958603388398887, Train accuracy 0.91146, Test loss
0.41934661067724227, Test accuracy 0.8616, NoLabel Accuracy 51.4599999999999
94
Epoch 30, Train loss 0.2469574574407935, Train accuracy 0.91274, Test loss
0.43635995832383634, Test accuracy 0.8558, NoLabel Accuracy 52.33
Epoch 31, Train loss 0.23779281569600105, Train accuracy 0.91778, Test loss
0.43050874363482, Test accuracy 0.8557, NoLabel Accuracy 53.6
Epoch 32, Train loss 0.2292194628391415, Train accuracy 0.9195, Test loss 0.
4057857525393367, Test accuracy 0.8646, NoLabel Accuracy 54.35
Epoch 33, Train loss 0.22133019650708885, Train accuracy 0.92218, Test loss
0.39317816500514746, Test accuracy 0.8694, NoLabel Accuracy 56.8200000000000
1
Epoch 34, Train loss 0.21131700300335884, Train accuracy 0.925, Test loss 0.
4045492551088333, Test accuracy 0.8713, NoLabel Accuracy 56.00000000000001
Epoch 35, Train loss 0.20280368482761085, Train accuracy 0.92898, Test loss
0.4001813688233495, Test accuracy 0.8659, NoLabel Accuracy 56.66
Epoch 36, Train loss 0.19795199086487295, Train accuracy 0.92934, Test loss
0.3875773511737585, Test accuracy 0.8736, NoLabel Accuracy 56.72000000000000
6
Epoch 37, Train loss 0.19136814153894782, Train accuracy 0.93328, Test loss
0.40164287349283695, Test accuracy 0.8699, NoLabel Accuracy 56.8899999999999
9
Epoch 38, Train loss 0.18078936842478813, Train accuracy 0.93656, Test loss
0.3980545503363013, Test accuracy 0.8709, NoLabel Accuracy 55.34
Epoch 39, Train loss 0.1762613302589953, Train accuracy 0.93902, Test loss
0.38579977177381514, Test accuracy 0.8755, NoLabel Accuracy 55.7799999999999
94
Epoch 40, Train loss 0.16939530287876725, Train accuracy 0.94044, Test loss
0.397768667177856, Test accuracy 0.8697, NoLabel Accuracy 55.269999999999996
Epoch 41, Train loss 0.16668343320444226, Train accuracy 0.94134, Test loss
0.38964408542886375, Test accuracy 0.8741, NoLabel Accuracy 55.75
Epoch 42, Train loss 0.16011176820661874, Train accuracy 0.94454, Test loss
0.38756698313578963, Test accuracy 0.8736, NoLabel Accuracy 54.36
Epoch 43, Train loss 0.15396924899458886, Train accuracy 0.94588, Test loss
0.38111162870526316, Test accuracy 0.8756, NoLabel Accuracy 56.54
Epoch 44, Train loss 0.14712750981446357, Train accuracy 0.94794, Test loss
0.3846097068145871, Test accuracy 0.8777, NoLabel Accuracy 55.94
Epoch 45, Train loss 0.14395980868637562, Train accuracy 0.94946, Test loss
0.37511624975204466, Test accuracy 0.8776, NoLabel Accuracy 55.19
Epoch 46, Train loss 0.1410141050895676, Train accuracy 0.95124, Test loss
0.36263283863365653, Test accuracy 0.8823, NoLabel Accuracy 56.4899999999999
95
Epoch 47, Train loss 0.13488670786011964, Train accuracy 0.95336, Test loss
0.37289379360228775, Test accuracy 0.8795, NoLabel Accuracy 55.87
Epoch 48, Train loss 0.13136343899350614, Train accuracy 0.954, Test loss 0.
3748378746725619, Test accuracy 0.8789, NoLabel Accuracy 55.669999999999995
Epoch 49, Train loss 0.1308792077526264, Train accuracy 0.95426, Test loss
0.3734875489644706, Test accuracy 0.8799, NoLabel Accuracy 55.41000000000000
```

```
4
Epoch 50, Train loss 0.12566706750977785, Train accuracy 0.95676, Test loss
0.37194543466791513, Test accuracy 0.8821, NoLabel Accuracy 56.8999999999999
9
Epoch 51, Train loss 0.12422420908432454, Train accuracy 0.95728, Test loss
0.37819664292261007, Test accuracy 0.8776, NoLabel Accuracy 56.43
Epoch 52, Train loss 0.12539945043623446, Train accuracy 0.9577, Test loss
0.37442457415908575, Test accuracy 0.8824, NoLabel Accuracy 56.42
Epoch 53, Train loss 0.12033280499543994, Train accuracy 0.95804, Test loss
0.3682648988887668, Test accuracy 0.8821, NoLabel Accuracy 56.42
Epoch 54, Train loss 0.12072094284471124, Train accuracy 0.95826, Test loss
0.3634823924150318, Test accuracy 0.884, NoLabel Accuracy 56.18
Epoch 55, Train loss 0.11805840330667794, Train accuracy 0.95942, Test loss
0.37241467096805575, Test accuracy 0.8809, NoLabel Accuracy 56.46
Epoch 56, Train loss 0.11670963669043034, Train accuracy 0.95898, Test loss
0.3693078789971769, Test accuracy 0.8838, NoLabel Accuracy 56.57
Epoch 57, Train loss 0.11667076341520995, Train accuracy 0.96014, Test loss
0.35885330810397864, Test accuracy 0.8843, NoLabel Accuracy 56.7200000000000
06
Epoch 58, Train loss 0.11490545755714178, Train accuracy 0.96076, Test loss
0.3722071375776082, Test accuracy 0.8824, NoLabel Accuracy 56.64
Epoch 59, Train loss 0.11323038229238241, Train accuracy 0.96176, Test loss
0.36542561520338057, Test accuracy 0.8844, NoLabel Accuracy 56.65
```

In [29]:

```python
# No time to implement the model checkppoint code as it is not asked in the

# Define the checkpoint directory
# checkpoint_dir = "checkpoints"
# os.makedirs(checkpoint_dir, exist_ok=True)

# # Training loop
# for epoch in range(num_epochs):
#     # Training code here...

#     # Save a checkpoint
#     checkpoint = {
#         "epoch": epoch,
#         "model_state_dict": model.state_dict(),
#         "optimizer_state_dict": optimizer.state_dict(),
#         "loss": loss,
#     }
#     torch.save(checkpoint, os.path.join(checkpoint_dir, f"checkpoint_{epoc
```

In [17]:

```python
model.eval()
```

Out[17]:
```
ResNet(
  (conv1): Conv2d(3, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1),
bias=False)
  (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_runnin
g_stats=True)
  (layer1): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=
(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_ru
nning_stats=True)
      (dropout1): Dropout2d(p=0.3, inplace=False)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=
(1, 1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_ru
nning_stats=True)
      (dropout2): Dropout2d(p=0.3, inplace=False)
      (shortcut): Sequential()
    )
  )
  (layer2): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(64, 128, kernel_size=(3, 3), stride=(2, 2), padding=
(1, 1), bias=False)
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_r
unning_stats=True)
      (dropout1): Dropout2d(p=0.3, inplace=False)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=
(1, 1), bias=False)
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_r
unning_stats=True)
      (dropout2): Dropout2d(p=0.3, inplace=False)
      (shortcut): Sequential(
        (0): Conv2d(64, 128, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_r
unning_stats=True)
      )
    )
  )
  (layer3): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(128, 256, kernel_size=(3, 3), stride=(2, 2), padding=
(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_r
unning_stats=True)
      (dropout1): Dropout2d(p=0.3, inplace=False)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=
(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_r
unning_stats=True)
      (dropout2): Dropout2d(p=0.3, inplace=False)
      (shortcut): Sequential(
        (0): Conv2d(128, 256, kernel_size=(1, 1), stride=(2, 2), bias=Fals
e)
        (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_r
unning_stats=True)
```

```
        )
      )
    )
    (layer4): Sequential(
      (0): BasicBlock(
        (conv1): Conv2d(256, 512, kernel_size=(3, 3), stride=(2, 2), padding=
(1, 1), bias=False)
        (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_r
unning_stats=True)
        (dropout1): Dropout2d(p=0.3, inplace=False)
        (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=
(1, 1), bias=False)
        (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_r
unning_stats=True)
        (dropout2): Dropout2d(p=0.3, inplace=False)
        (shortcut): Sequential(
          (0): Conv2d(256, 512, kernel_size=(1, 1), stride=(2, 2), bias=Fals
e)
          (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_r
unning_stats=True)
        )
      )
    )
    (linear): Linear(in_features=512, out_features=10, bias=True)
  )
```

In [18]:

```
predictions = []
# model.eval()
for image in kaggleLoader:
    image = image.cuda()
    with torch.no_grad():
        output = model(image)
    predictions.append(output.argmax().item())
curr_acc = calculate_accuracy(predictions)
```

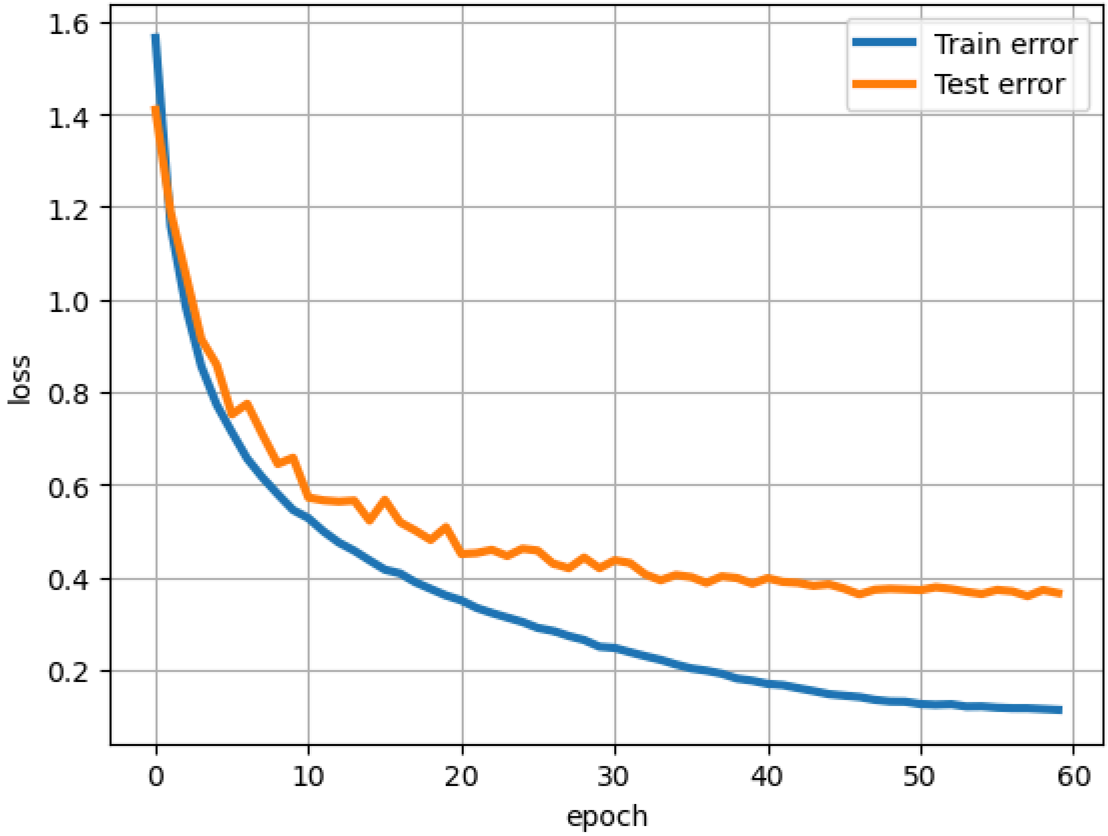
In [19]:

```
torch.save(model.state_dict(), 'learn_rate_consistent_model.pth')
name_file = "learn_rate_const_lr_" + str(learn_rate) + ".txt"
with open(name_file, 'w') as file:
    for row in [train_loss_history, test_loss_history]:
        file.write('\t'.join(map(str, row)) + '\n')
print("finished round " + str(learn_rate) + " with ACC of " + str(curr_acc))
print("done")
```

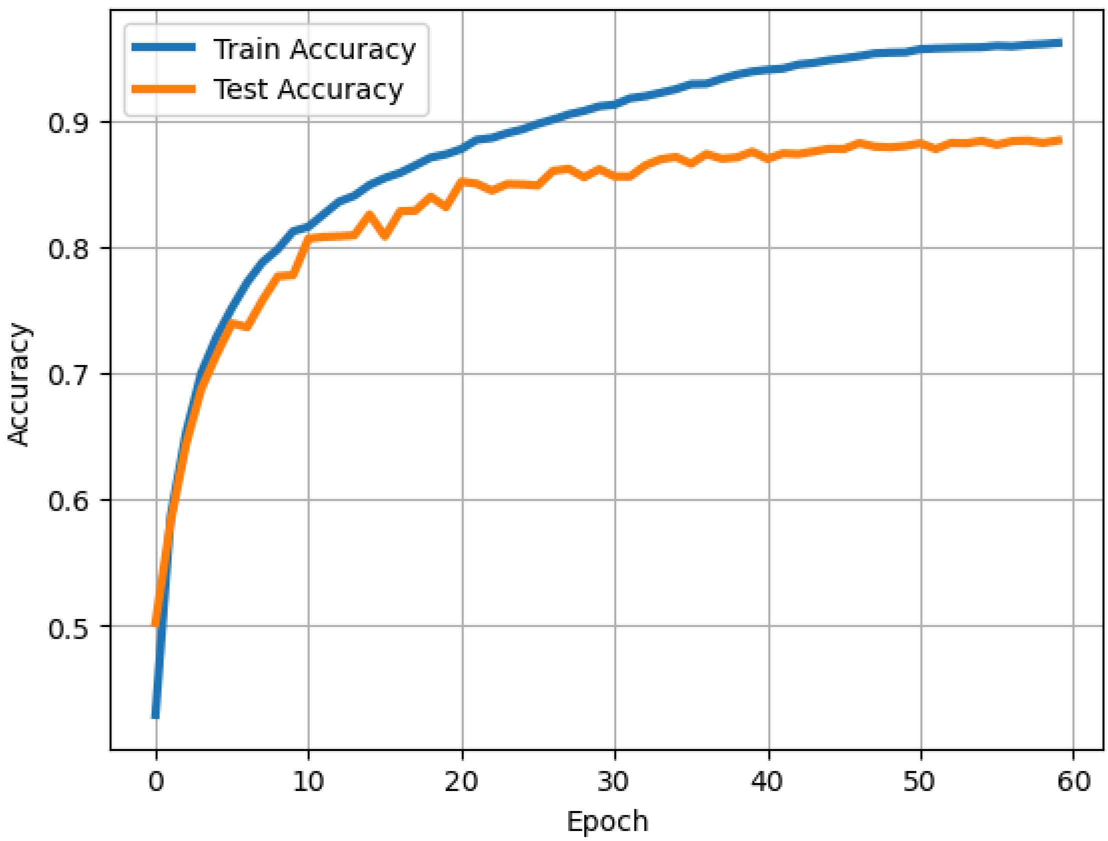
```
finished round 0.004 with ACC of 66.22
done
```

In [20]:

```
plt.plot(range(len(train_loss_history)),train_loss_history,'-',linewidth=3,l
plt.plot(range(len(test_loss_history)),test_loss_history,'-',linewidth=3,lab
plt.xlabel('epoch')
plt.ylabel('loss')
plt.grid(True)
plt.legend()
plt.show()
```



In [21]:
```
plt.plot(range(len(train_accuracy_history)),train_accuracy_history,'-',linew
plt.plot(range(len(test_accuracy_history)),test_accuracy_history,'-',linewic
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.grid(True)
plt.legend()
plt.show()
```



In [32]:
```
model.load_state_dict(torch.load('learn_rate_consistent_model.pth'))
```

Out[32]: <All keys matched successfully>

In [33]:
```
correct = 0
total = 0
model.eval()
for data in testDataLoader:
    images, labels = data
    images = images.cuda()
    labels = labels.cuda()
    with torch.no_grad():
        predicted_output = model(images)
        _, predicted = torch.max(predicted_output.data, 1)
        total += labels.size(0)
        correct += (predicted == labels).sum().item()

accuracy = correct / total
print('Accuracy of the network on the test images: %d %%' % (100 * accuracy)
```

Accuracy of the network on the test images: 92 %

In [22]:
```
def count_parameters(model):
    """
    Counts the number of trainable and non-trainable parameters in a PyTorch
    """
    total_params = sum(p.numel() for p in model.parameters())
    trainable_params = sum(p.numel() for p in model.parameters() if p.requir
    non_trainable_params = total_params - trainable_params
```

```
    print(f"Total parameters: {total_params}")
    print(f"Trainable parameters: {trainable_params}")
    print(f"Non-trainable parameters: {non_trainable_params}")
```

In [28]:
```
count_parameters(model)
```

```
Total parameters: 4903242
Trainable parameters: 4903242
Non-trainable parameters: 0
```

In [34]:
```
pip install nbconvert
```

```
Defaulting to user installation because normal site-packages is not writeabl
e
Requirement already satisfied: nbconvert in /share/apps/anaconda3/2024.02/li
b/python3.11/site-packages (7.10.0)
Requirement already satisfied: beautifulsoup4 in /share/apps/anaconda3/2024.
02/lib/python3.11/site-packages (from nbconvert) (4.12.2)
Requirement already satisfied: bleach!=5.0.0 in /share/apps/anaconda3/2024.0
2/lib/python3.11/site-packages (from nbconvert) (4.1.0)
Requirement already satisfied: defusedxml in /share/apps/anaconda3/2024.02/l
ib/python3.11/site-packages (from nbconvert) (0.7.1)
Requirement already satisfied: jinja2>=3.0 in /share/apps/anaconda3/2024.02/
lib/python3.11/site-packages (from nbconvert) (3.1.3)
Requirement already satisfied: jupyter-core>=4.7 in /share/apps/anaconda3/20
24.02/lib/python3.11/site-packages (from nbconvert) (5.5.0)
Requirement already satisfied: jupyterlab-pygments in /share/apps/anaconda3/
2024.02/lib/python3.11/site-packages (from nbconvert) (0.1.2)
Requirement already satisfied: markupsafe>=2.0 in /share/apps/anaconda3/202
4.02/lib/python3.11/site-packages (from nbconvert) (2.1.3)
Requirement already satisfied: mistune<4,>=2.0.3 in /share/apps/anaconda3/20
24.02/lib/python3.11/site-packages (from nbconvert) (2.0.4)
Requirement already satisfied: nbclient>=0.5.0 in /share/apps/anaconda3/202
4.02/lib/python3.11/site-packages (from nbconvert) (0.8.0)
Requirement already satisfied: nbformat>=5.7 in /share/apps/anaconda3/2024.0
2/lib/python3.11/site-packages (from nbconvert) (5.9.2)
Requirement already satisfied: packaging in /share/apps/anaconda3/2024.02/li
b/python3.11/site-packages (from nbconvert) (23.1)
Requirement already satisfied: pandocfilters>=1.4.1 in /share/apps/anaconda
3/2024.02/lib/python3.11/site-packages (from nbconvert) (1.5.0)
Requirement already satisfied: pygments>=2.4.1 in /share/apps/anaconda3/202
4.02/lib/python3.11/site-packages (from nbconvert) (2.15.1)
Requirement already satisfied: tinycss2 in /share/apps/anaconda3/2024.02/li
b/python3.11/site-packages (from nbconvert) (1.2.1)
Requirement already satisfied: traitlets>=5.1 in /share/apps/anaconda3/2024.
02/lib/python3.11/site-packages (from nbconvert) (5.7.1)
Requirement already satisfied: six>=1.9.0 in /share/apps/anaconda3/2024.02/l
ib/python3.11/site-packages (from bleach!=5.0.0->nbconvert) (1.16.0)
Requirement already satisfied: webencodings in /share/apps/anaconda3/2024.0
2/lib/python3.11/site-packages (from bleach!=5.0.0->nbconvert) (0.5.1)
Requirement already satisfied: platformdirs>=2.5 in /share/apps/anaconda3/20
24.02/lib/python3.11/site-packages (from jupyter-core>=4.7->nbconvert) (3.1
0.0)
Requirement already satisfied: jupyter-client>=6.1.12 in /share/apps/anacond
a3/2024.02/lib/python3.11/site-packages (from nbclient>=0.5.0->nbconvert)
(8.6.0)
Requirement already satisfied: fastjsonschema in /share/apps/anaconda3/2024.
02/lib/python3.11/site-packages (from nbformat>=5.7->nbconvert) (2.16.2)
Requirement already satisfied: jsonschema>=2.6 in /share/apps/anaconda3/202
4.02/lib/python3.11/site-packages (from nbformat>=5.7->nbconvert) (4.19.2)
Requirement already satisfied: soupsieve>1.2 in /share/apps/anaconda3/2024.0
2/lib/python3.11/site-packages (from beautifulsoup4->nbconvert) (2.5)
Requirement already satisfied: attrs>=22.2.0 in /share/apps/anaconda3/2024.0
2/lib/python3.11/site-packages (from jsonschema>=2.6->nbformat>=5.7->nbconve
rt) (23.1.0)
Requirement already satisfied: jsonschema-specifications>=2023.03.6 in /shar
e/apps/anaconda3/2024.02/lib/python3.11/site-packages (from jsonschema>=2.6-
>nbformat>=5.7->nbconvert) (2023.7.1)
```

```
Requirement already satisfied: referencing>=0.28.4 in /share/apps/anaconda3/2024.02/lib/python3.11/site-packages (from jsonschema>=2.6->nbformat>=5.7->nbconvert) (0.30.2)
Requirement already satisfied: rpds-py>=0.7.1 in /share/apps/anaconda3/2024.02/lib/python3.11/site-packages (from jsonschema>=2.6->nbformat>=5.7->nbconvert) (0.10.6)
Requirement already satisfied: python-dateutil>=2.8.2 in /share/apps/anaconda3/2024.02/lib/python3.11/site-packages (from jupyter-client>=6.1.12->nbclient>=0.5.0->nbconvert) (2.8.2)
Requirement already satisfied: pyzmq>=23.0 in /share/apps/anaconda3/2024.02/lib/python3.11/site-packages (from jupyter-client>=6.1.12->nbclient>=0.5.0->nbconvert) (25.1.2)
Requirement already satisfied: tornado>=6.2 in /share/apps/anaconda3/2024.02/lib/python3.11/site-packages (from jupyter-client>=6.1.12->nbclient>=0.5.0->nbconvert) (6.3.3)
Note: you may need to restart the kernel to use updated packages.
```

In [ ]: