Bayesian Neural Networks

We used a BCNN layer implementation from a github repo by Kumar Shridhar based on a paper....

Required packages

- `torch`
- `torchvision`
- `seaborn`
- `numby`
- `tensorboard`
- `matplotlib`

Setup

Below is code that imports the libraries, sets the device, imports the data, and the function for training.

In [1]:
```
# Pytorch libraries
import torch
import torch.nn as nn
import torch.optim as optim
import torchvision
torchvision.disable_beta_transforms_warning()
import torchvision.transforms.v2 as transforms
import torch.utils.tensorboard as tb
import torch.nn.functional as F

# Code from paper
from BCNN.layers.misc import ModuleWrapper
from BCNN.layers.BBB import BBBConv
from BCNN.layers.BBB import BBBLinear

from sklearn.metrics import confusion_matrix
import seaborn as sn
import pandas as pd
import tensorboard
import matplotlib.ticker as mticker

import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
%config InlineRenderer.figure_format = 'retina'
```

```python
# Directory for logging
log_dir = 'logs'


# Device setup
device = torch.device("cuda" if torch.cuda.is_available() else "mps" if torc

print(f"Using device: {device}") # Print device

transform = transforms.Compose([
    transforms.ToImage(),
    transforms.ConvertImageDtype(),
    # Depending on torchvision version you may need to change these:
    # - If you don't have torchvision.transforms.v2, then import torchvision
    #   instead and use ToTensor() to replace _both_ of the transforms above
    # - If you have v2 but it says ToImage() is undefined, then use ToImageT
])

cifar = torchvision.datasets.CIFAR10("cifar", download=True, transform=trans
train_size = int((5/6) * len(cifar)) # 5/6 split of data
train_data, valid_data = torch.utils.data.random_split(cifar, [train_size, l

classes = ['plane', 'car', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse', 's

# For data normalization
cifar_mean = (0.4914, 0.4822, 0.4465)
cifar_std = (0.2470, 0.2435, 0.2616)
mean = []
for x, _ in cifar:
    mean.append(torch.mean(x, dim=(1, 2)))
mean = torch.stack(mean, dim=0).mean(dim=0)
std = []
for x, _ in cifar:
    std.append(((x - mean[:,np.newaxis,np.newaxis]) ** 2).mean(dim=(1, 2)))
std = torch.stack(std, dim=0).mean(dim=0).sqrt()

# Data augmentation
normalize = transforms.Normalize(cifar_mean, cifar_std)
augments = transforms.Compose([
            transforms.RandomHorizontalFlip(0.05),
            transforms.RandomGrayscale(0.03),
            transforms.ColorJitter(
                brightness=0.08,
                contrast=0.031,
                saturation=0.031,
                hue=0),
            transforms.Normalize(cifar_mean, cifar_std)
        ])

# Train function
def train(  model_class = None, # Model type
            model_type = "", # String for logging
            lr = 1e-3, # Learning rate
            epochs = 10, # Epochs
            reg = 0, # Regularization
            train_batch_size = 32, # Train batch size
```

```
        val_batch_size = 1000): # Validation batch size

    # Data loaders
    data_loader = torch.utils.data.DataLoader(train_data, batch_size=train_b
    valid_loader = torch.utils.data.DataLoader(valid_data, batch_size=val_ba

    # Tracking accuracy over time
    train_accs = []
    valid_accs = []

    # Init model to device
    network = model_class().to(device)
    logger = tb.SummaryWriter(log_dir + '/' + model_type + '-lr-' + str(lr)
    loss = nn.CrossEntropyLoss() # Loss function

    opt = optim.AdamW(network.parameters(), lr=lr, weight_decay=reg) # Setup
    scheduler = optim.lr_scheduler.StepLR(opt, step_size=20, gamma=0.85) # S

    global_step = 0 # Steps for logging
    for i in range(epochs):
        train_acc = []
        network.train()
        # The data loader makes batching easy
        for batch_xs, batch_ys in data_loader:
            batch_xs = batch_xs.to(device)
            preds = network(augments(batch_xs))
            loss_val = loss(preds, batch_ys.to(device))


            # Reset the gradients of all of parameters
            opt.zero_grad()
            # backward() call computes gradients using backpropagation
            loss_val.backward()
            # step() changes the parameters.
            opt.step()
            preds = network(normalize(batch_xs))
            train_acc.append((preds.argmax(dim=1) == batch_ys.to(device)).fl
            # Logging
            logger.add_scalar('loss', loss_val, global_step=global_step)
            logger.add_scalar('training accuracy', (preds.argmax(dim=1) == b
            global_step += 1

        train_accs.append(np.mean([tensor.item() for tensor in train_acc]))

        # Mesaure the validation accuracy.
        network.eval()
        val_acc = []
        for batch_xs, batch_ys in valid_loader:
            preds = network(normalize(batch_xs.to(device)))
            val_acc.append((preds.argmax(dim=1) == batch_ys.to(device)).floa

        valid_accs.append(np.mean([tensor.item() for tensor in val_acc]))
        logger.add_scalar('validation accuracy', valid_accs[-1], global_step

        scheduler.step() # Iterate step
```

```
        print("Epoch:", i + 1, "\nTrain accuracy:", train_accs[-1], "\nValid

    return network, train_accs, valid_accs # Return model
```

Models

Below is the code that defines out CNN and a bayesian CNN model. They are intentionally the similar structure.

In [2]:

```
class CNN(nn.Module):
    def __init__(self, arch=None, activation=F.relu):
        super().__init__()
        # Code from pytorch site
        self.activation = activation
        self.conv1 =  nn.Conv2d(3, 6, 5) # Could also add stridding and padd
        self.pool = nn.MaxPool2d(2, 2)
        self.conv2 = nn.Conv2d(6, 16, 5)
        self.fc1 = nn.Linear(16 * 5 * 5, 120)
        self.fc2 = nn.Linear(120, 84)
        self.fc3 = nn.Linear(84, 10)
        self.dropout = nn.Dropout(0.05)

    def forward(self, x):
        x = self.pool(self.activation(self.conv1(x)))
        x = self.pool(self.activation(self.conv2(x)))
        x = torch.flatten(x, 1) # flatten all dimensions except batch
        x = self.dropout(x)
        x = self.activation(self.fc1(x))
        x = self.dropout(x)
        x = self.activation(self.fc2(x))
        x = self.fc3(x)
        return x
```

In [3]:

```
class BNN(ModuleWrapper):
  def __init__(self, activation=F.relu):
    super().__init__()
    self.activation = activation
    self.conv1 = BBBConv.BBBConv2d(3, 6, 5)
    self.pool = nn.MaxPool2d(2, 2)
    self.conv2 = BBBConv.BBBConv2d(6, 16, 5)
    self.fc1 = BBBLinear.BBBLinear(16 * 5 * 5, 120)
    self.fc2 = BBBLinear.BBBLinear(120, 84)
    self.fc3 = BBBLinear.BBBLinear(84, 10)
    self.dropout = nn.Dropout(0.05)


  def forward(self, x):
    x = self.pool(self.activation(self.conv1(x)))
    x = self.pool(self.activation(self.conv2(x)))
    x = torch.flatten(x, 1) # flatten all dimensions except batch
    x = self.dropout(x)
    x = self.activation(self.fc1(x))
    x = self.dropout(x)
```

```
    x = self.activation(self.fc2(x))
    x = self.fc3(x)
    return x
```

Training

The code chunks below trains the CNN and BCNN model. Both models use the same `train` function which takes the following inputs:

- `model_class` : The type of model to be trained.
- `model_type` : This is a string that is used for logging purposes. Changing it while only change the tensorboard visualisation.
- `lr` : Learning rate. A larger number...
- `reg` : Regularization...
- `epochs` : Epochs for training.
- `train_batch_size` : Training batch size. the number is small for accuracy purposes, but large for train time efficency purposes.
- `val_batch_size` : Validation batch size. It is intentionally larger than the train batch size because

In [ ]:
```
cnn_model, cnn_train_acc, cnn_val_acc = train( model_class=CNN,
                    model_type = "CNN",
                    lr=0.001,
                    reg=0.001,
                    epochs=100,
                    train_batch_size=32,
                    val_batch_size = 5000)
```

In [ ]:
```
bnn_model, bnn_train_acc, bnn_val_acc = train( model_class=BNN,
                    model_type = "BNN",
                    lr=0.003,
                    reg=0.001,
                    epochs=100,
                    train_batch_size=32,
                    val_batch_size = 5000)
```

Save and load models

Uncomment to save or load as necessary.

In [65]:
```
# torch.save(cnn_model.state_dict(), "Models/cnn_model.pt")
# torch.save(bnn_model.state_dict(), "Models/bnn_model.pt")
```

In [6]:
```
cnn_model = CNN()
cnn_model.load_state_dict(torch.load("Models/cnn_model.pt", map_location= de
cnn_model = cnn_model.to(device)
bnn_model = BNN()
```

```
bnn_model.load_state_dict(torch.load("Models/bnn_model.pt", map_location = d
bnn_model = bnn_model.to(device)
```

Check and Demo models

This section visualizes the training of the models in addition to the accuracy of the model.

In [ ]:
```
# This visualizes the loss of various model during training

# Reload extension, you may need to run this chunk multiple times

%reload_ext tensorboard

# Load the tensorboard extension for Jupyter
%load_ext tensorboard
# Start tensorboard and tell it where to look for logs. It will auto-update
%tensorboard --logdir {log_dir} --reload_interval 1
```

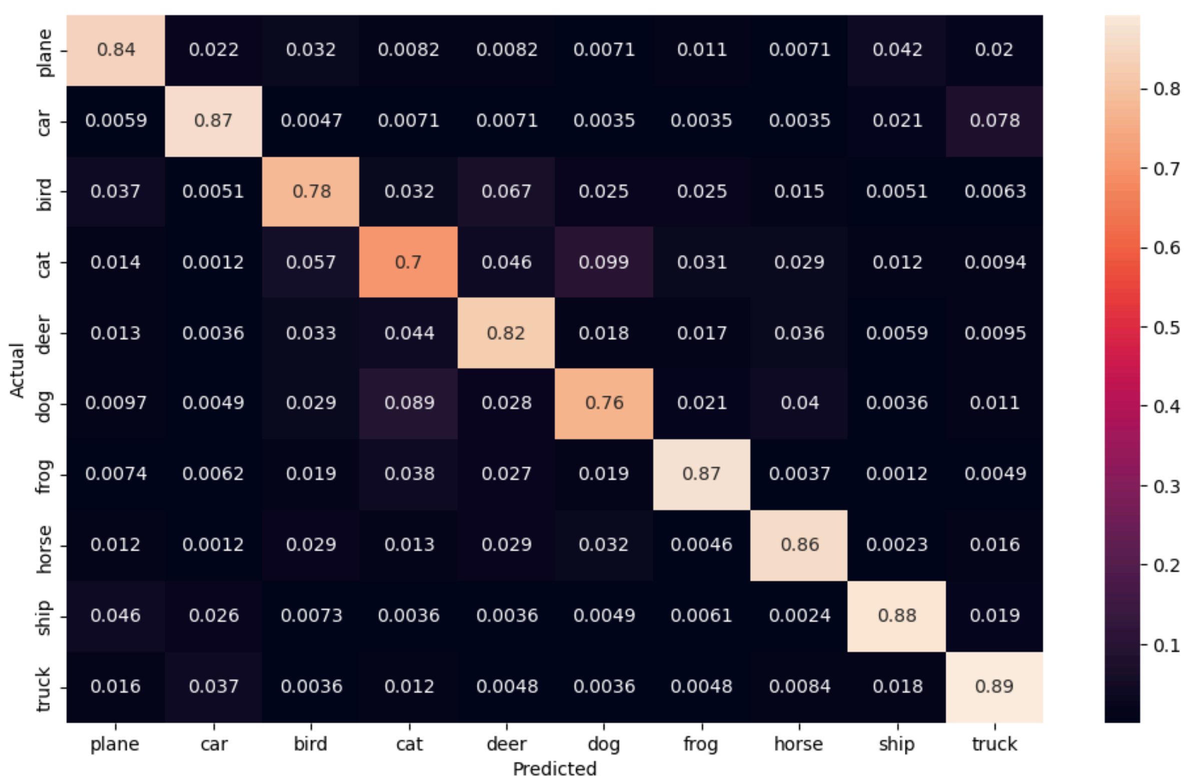
In [7]:
```
# This section runs predictions on the validation data for
valid_loader = torch.utils.data.DataLoader(valid_data, batch_size=5000, shuf

#cnn_model.eval() # set model to eval mode
#bnn_model.eval() # set model to eval mode

actual = []
cnn_softmaxes = []
cnn_preds = []
bnn_softmaxes = []
bnn_preds = []

for batch_xs, batch_ys in valid_loader:
    cnn_softmaxes += cnn_model(normalize(batch_xs.to(device))).tolist()
    cnn_preds += cnn_model(normalize(batch_xs.to(device))).argmax(dim=1).tol
    actual += batch_ys.tolist()

for batch_xs, _ in valid_loader:
    bnn_softmaxes += bnn_model(normalize(batch_xs.to(device))).tolist()
    bnn_preds += bnn_model(normalize(batch_xs.to(device))).argmax(dim=1).tol
```

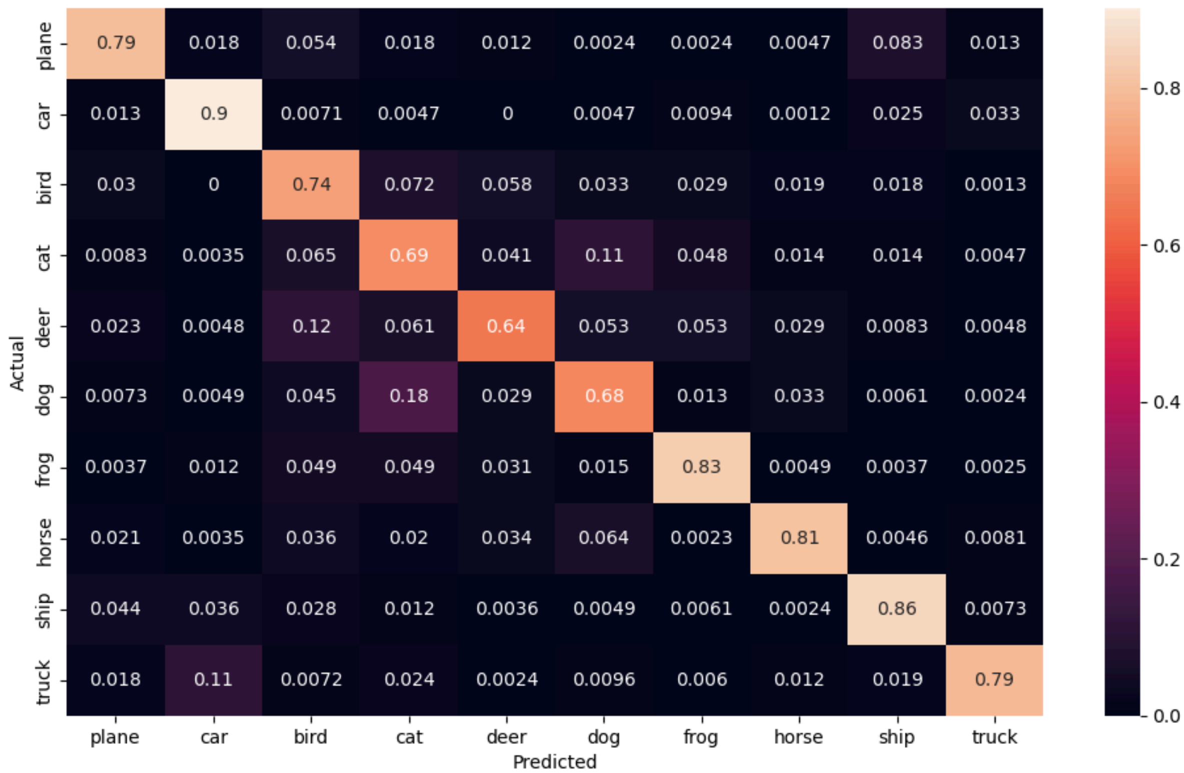
In [ ]:
```
def pretty_graph(train_acc, val_acc, type):
    epochs = len(train_acc)
    train_acc = [tensor.item() for tensor in train_acc]
    val_acc = [tensor.item() for tensor in val_acc]
    ax = plt.gca()
    ax.set_ylim([0, 1])
    plt.plot(list(range(1, 1 + epochs)), train_acc, label = "Train Accuracy"
    plt.plot(list(range(1, 1 + epochs)), val_acc, label = "Validation Accura
    plt.gca().set_yticklabels([f'{x:.0%}' for x in plt.gca().get_yticks()])
    plt.gca().xaxis.set_major_locator(mticker.MultipleLocator(1))
    plt.legend()
    plt.title("Validation vs Train accuracy (" + type + ")")
    plt.xlabel("Epoch")
    plt.ylabel("Accuracy %")
```

```
    ax.xaxis.set_major_locator(plt.MaxNLocator(11))
    #plt.savefig('Images/' + type + '_val_acc_over_time.png', transparent=Tr
    plt.show()

pretty_graph(cnn_train_acc, cnn_val_acc, "CNN")
pretty_graph(bnn_train_acc, bnn_val_acc, "BNN")
```

In [8]:
```
cnn_cf_matrix = confusion_matrix(actual, cnn_preds)
bnn_cf_matrix = confusion_matrix(actual, bnn_preds)

df_cnn_cm = pd.DataFrame(cnn_cf_matrix / np.sum(cnn_cf_matrix, axis=1)[:, No
                     columns = [i for i in classes])

df_bnn_cm = pd.DataFrame(bnn_cf_matrix / np.sum(bnn_cf_matrix, axis=1)[:, No
                     columns = [i for i in classes])

plt.figure(figsize = (12,7))
sn.heatmap(df_cnn_cm, annot=True)
plt.xlabel("Predicted")
plt.ylabel("Actual")
#plt.savefig('Images/CNN_confusion_matrix.png', transparent=True) # Save fig
plt.plot()

plt.figure(figsize = (12,7))
sn.heatmap(df_bnn_cm, annot=True)
plt.xlabel("Predicted")
plt.ylabel("Actual")
#plt.savefig('Images/BNN_confusion_matrix.png', transparent=True) # Save fig
plt.plot()
```

Out[8]: []





In [115…

```
import random
import math

fig, axs = plt.subplots(1, 5, figsize=(13, 13))
sample = random.sample(range(1, len(valid_data)), 5)

softmax = lambda x : math.e **(x - np.max(x)) / np.sum(math.e**(x - np.max(x

for i in range(5):
    r = sample[i]
    axs[i].imshow(valid_data[r][0].numpy().transpose(1, 2, 0))
    cnn_pred = cnn_preds[r]
    cnn_certainty = softmax(np.array(cnn_softmaxes[r]))
    bnn_pred = bnn_preds[r]
    bnn_certainty = softmax(np.array(bnn_softmaxes[r]))
    axs[i].set_title("CNN: {} ({:.2f}) \n BCNN: {} ({:.2f})".format(classes[
plt.show()
```