Neural net implementation

For my final implementation, I'm going to use a neural net. Depending on performance, I may mix things up and use my neural net as a feature extractor which I then feed into perceptron or svm or logistic regression.

I'll try the neural net accross the different datasets.

```
import torch
import torch.nn as nn
import torch.nn.functional as Func
from torch.utils.data import DataLoader
from torch.utils.data import Dataset
import numpy as np
import pandas as pd
import time
from datetime import datetime

from sklearn.ensemble import RandomForestClassifier

import torchvision
import torchvision.transforms.functional as F
import random
import numbers
import copy

import matplotlib.pyplot as plt
from IPython.display import display
from matplotlib.pyplot import imshow
from matplotlib.colors import ListedColormap
%matplotlib inline

# from torch.optim.lr_scheduler import StepLR
from torch.optim import lr_scheduler
import os
from tqdm.notebook import tqdm
from torchvision import transforms

import torch.optim as optim
from torch.optim.lr_scheduler import LambdaLR


device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
print(device)
```

```
cuda:0
```

Initializing paths

```
# Initializing
```

```
# TRAINING_PATH = '/content/drive/My Drive/Colab Notebooks/Machine Learning 2020/old-bailey-de
# TESTING_PATH = '/content/drive/My Drive/Colab Notebooks/Machine Learning 2020/old-bailey-dec
# EVAL_PATH = '/content/drive/My Drive/Colab Notebooks/Machine Learning 2020/old-bailey-decisi

#MISC V2
TRAINING_PATH = '/content/drive/My Drive/Colab Notebooks/Machine Learning 2020/old-bailey-deci
TESTING_PATH = '/content/drive/My Drive/Colab Notebooks/Machine Learning 2020/old-bailey-decis
EVAL_PATH = '/content/drive/My Drive/Colab Notebooks/Machine Learning 2020/old-bailey-decision

TRAINING_PATH_GLOVE = '/content/drive/My Drive/Colab Notebooks/Machine Learning 2020/old-baile
TESTING_PATH_GLOVE = '/content/drive/My Drive/Colab Notebooks/Machine Learning 2020/old-bailey
EVAL_PATH_GLOVE = '/content/drive/My Drive/Colab Notebooks/Machine Learning 2020/old-bailey-de

# TRAINING_PATH_TF = '/content/drive/My Drive/Colab Notebooks/Machine Learning 2020/old-bailey
# TESTING_PATH_TF = '/content/drive/My Drive/Colab Notebooks/Machine Learning 2020/old-bailey-
# EVAL_PATH_TF = '/content/drive/My Drive/Colab Notebooks/Machine Learning 2020/old-bailey-dec

# TF V2
TRAINING_PATH_TF = '/content/drive/My Drive/Colab Notebooks/Machine Learning 2020/old-bailey-d
TESTING_PATH_TF = '/content/drive/My Drive/Colab Notebooks/Machine Learning 2020/old-bailey-de
EVAL_PATH_TF = '/content/drive/My Drive/Colab Notebooks/Machine Learning 2020/old-bailey-decis

TRAINING_PATH_BOW = '/content/drive/My Drive/Colab Notebooks/Machine Learning 2020/old-bailey-
TESTING_PATH_BOW = '/content/drive/My Drive/Colab Notebooks/Machine Learning 2020/old-bailey-d
EVAL_PATH_BOW = '/content/drive/My Drive/Colab Notebooks/Machine Learning 2020/old-bailey-deci

EVAL_IDS = '/content/drive/My Drive/Colab Notebooks/Machine Learning 2020/old-bailey-decisions
```

Loading data

Creating a custom dataset: https://pytorch.org/tutorials/beginner/data_loading_tutorial.html

```
# Create a custom dataset class

class OldBaileyData(Dataset):
    """Old Bailey Decisions data."""

    def __init__(self, csv_file, transform=None):
        """
        Args:
            csv_file (string): Path to the csv file in question.
            transform (callable, optional): Optional transform to be applied
                on a sample.
        """
        self.data = pd.read_csv(csv_file).to_numpy()
        self.transform = transform

    def __len__(self):
        return len(self.data)

    def __getitem__(self, idx):
        if torch.is_tensor(idx):
            idx = idx.tolist()
```

```
        X = self.data[idx,1:]
        y = self.data[idx,0]

        # change -1 y's to 0 -- maybe don't need.
        if y == -1:
          y = 0.0

        # Changing to tensor here b/c you can't use transforms = transforms.ToTensor() w/ non-
        sample = {'X': torch.from_numpy(X).type(torch.FloatTensor), 'y': torch.tensor(y).type(

        if self.transform:
            sample = self.transform(sample)

        return sample
```

Load data into dataset class.

```
%time train_data = OldBaileyData(csv_file=TRAINING_PATH_TF)
# I'm just gonna go ahead and use my test data as my validation data. I know this isn't super
%time val_data = OldBaileyData(csv_file=TESTING_PATH_TF)
%time eval_data = OldBaileyData(csv_file=EVAL_PATH_TF)

# MISC DATA
# %time train_data_m = OldBaileyData(csv_file=TRAINING_PATH)
# %time val_data_m = OldBaileyData(csv_file=TESTING_PATH)

print("Training length: ",len(train_data),"Val length: ",len(val_data))
```

```
CPU times: user 58 s, sys: 2.27 s, total: 1min
Wall time: 1min
CPU times: user 7.98 s, sys: 162 ms, total: 8.14 s
Wall time: 8.2 s
CPU times: user 18.1 s, sys: 314 ms, total: 18.4 s
Wall time: 20.5 s
Training length:  17500 Val length:  2250
```

```
# View a few examples
for i in range(10):
    sample = train_data[i]

    print(i, sample['X'].shape, sample['y'])
```

```
0 torch.Size([10051]) tensor(0.)
1 torch.Size([10051]) tensor(0.)
2 torch.Size([10051]) tensor(1.)
3 torch.Size([10051]) tensor(1.)
4 torch.Size([10051]) tensor(0.)
5 torch.Size([10051]) tensor(0.)
6 torch.Size([10051]) tensor(0.)
7 torch.Size([10051]) tensor(0.)
8 torch.Size([10051]) tensor(0.)
9 torch.Size([10051]) tensor(0.)
```

Create a data loader

```
# Create data loaders
batch_size = 256
# batch_size = 1 # change to 1 for predictions/feat extraction

# sample_train = list(range(0, len(train_data), 100))
# sample_val = list(range(0, len(val_data), 10))

# sampled_train = torch.utils.data.Subset(train_data, sample_train)
# sampled_val = torch.utils.data.Subset(val_data, sample_val)

# # Sample of data
# train_loader = DataLoader(
#   sampled_train, batch_size=batch_size, shuffle=True, drop_last=True) #, num_workers=2)

# val_loader = DataLoader(
#     sampled_val, batch_size=batch_size, shuffle=False) #, num_workers=2)

# Full dataset
train_loader = DataLoader(
  train_data, batch_size=batch_size, shuffle=True, drop_last=True)

val_loader = DataLoader(
    val_data, batch_size=batch_size, shuffle=False)

eval_loader = DataLoader(
    eval_data, batch_size=batch_size, shuffle=False)

# Full dataset misc
# train_loader_m = DataLoader(
#   train_data_m, batch_size=batch_size, shuffle=True, drop_last=True)

# val_loader_m = DataLoader(
#     val_data_m, batch_size=batch_size, shuffle=False)
```

Define my model

Because this is a simple case, I'll use the sequential API

Initializing weights using sequential: https://discuss.pytorch.org/t/initialising-weights-in-nn-sequential/76553

Other useful links:

1. https://discuss.pytorch.org/t/how-to-initialize-weights-in-nn-sequential-container/8534
2. https://pytorch.org/tutorials/beginner/nlp/deep_learning_tutorial.html
3. https://towardsdatascience.com/pytorch-tabular-binary-classification-a0368da5bb89

Experiment with using batchnorm and dropout.

```
# TF-IDF
```

```
in_features = train_data[0]['X'].size()[0]
print("input features: ",in_features)

#MISC
# in_features = train_data_m[0]['X'].size()[0]
# print("input features: ",in_features)

# Let's first begin with something simple

# This is pretty good, got me to 84.8%
# model = nn.Sequential(
#     nn.Linear(in_features=in_features,out_features=1000),
#     nn.BatchNorm1d(1000),
#     nn.ReLU(),
#     nn.Dropout(0.8),
#     nn.Linear(1000,100),
#     nn.BatchNorm1d(100),
#     nn.ReLU(),
#     nn.Dropout(0.8),
#     nn.Linear(100,1),
#     nn.Sigmoid()
# )

# # This is pretty good, got me to 85.0%
model = nn.Sequential(
    nn.Linear(in_features=in_features,out_features=1000),
    nn.BatchNorm1d(1000),
    nn.ReLU(),
    nn.Dropout(0.85),
    nn.Linear(1000,100),
    nn.BatchNorm1d(100),
    nn.ReLU(),
    nn.Dropout(0.8),
    nn.Linear(100,1),
    nn.Sigmoid()
)

# For glove
# model = nn.Sequential(
#     nn.Linear(in_features=in_features,out_features=100),
#     nn.BatchNorm1d(100),
#     nn.ReLU(),
#     nn.Dropout(0.5),
#     nn.Linear(100,50),
#     nn.BatchNorm1d(50),
#     nn.ReLU(),
#     nn.Dropout(0.5),
#     nn.Linear(50,1),
#     nn.Sigmoid()
# )

# model = nn.Sequential(
#     nn.Linear(in_features=in_features,out_features=1000),
#     nn.ReLU(),
#     nn.BatchNorm1d(1000),
#     nn.Dropout(0.85),
```

```
#     nn.Linear(1000,100),
#     nn.ReLU(),
#     nn.BatchNorm1d(100),
#     nn.Dropout(0.3),
#     nn.Linear(100,1),
#     nn.Sigmoid()
# )


# Lets go deeper
# model = nn.Sequential(
#     nn.Linear(in_features=in_features,out_features=5000),
#     nn.BatchNorm1d(5000),
#     nn.ReLU(),
#     nn.Dropout(0.5),
#     nn.Linear(5000,2500),
#     nn.BatchNorm1d(2500),
#     nn.ReLU(),
#     nn.Dropout(0.4),
#     nn.Linear(2500,1000),
#     nn.BatchNorm1d(1000),
#     nn.ReLU(),
#     nn.Dropout(0.3),
#     nn.Linear(1000,300),
#     nn.BatchNorm1d(300),
#     nn.ReLU(),
#     nn.Dropout(0.3),
#     nn.Linear(300,100),
#     nn.BatchNorm1d(100),
#     nn.ReLU(),
#     nn.Dropout(0.3),
#     nn.Linear(100,1),
#     nn.Sigmoid()
# )


# Misc Model
# model = nn.Sequential(
#     nn.Linear(in_features=in_features,out_features=50),
#     nn.BatchNorm1d(50),
#     nn.ReLU(),
#     nn.Dropout(0.1),
#     nn.Linear(50,20),
#     nn.BatchNorm1d(20),
#     nn.ReLU(),
#     nn.Dropout(0.1),
#     nn.Linear(20,1),
#     nn.Sigmoid()
# )


model.to(device)
print(model)
```

```
input features:  10051
```

```
Sequential(
  (0): Linear(in_features=10051, out_features=1000, bias=True)
  (1): BatchNorm1d(1000, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (2): ReLU()
  (3): Dropout(p=0.85, inplace=False)
  (4): Linear(in_features=1000, out_features=100, bias=True)
  (5): BatchNorm1d(100, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (6): ReLU()
  (7): Dropout(p=0.8, inplace=False)
  (8): Linear(in_features=100, out_features=1, bias=True)
  (9): Sigmoid()
)
```

Params + Optimizer + loss function

```
# model params
params_to_update = model.parameters()

# Define my loss function
# https://stackoverflow.com/questions/53628622/loss-function-its-inputs-for-binary-classificat
# criterion = nn.CrossEntropyLoss(reduction='mean')
criterion = nn.BCELoss()

# Optimizer
lr = 1e-3
optimizer = optim.Adam(params_to_update, lr=lr, betas=(0.9, 0.999))
# maybe adjust the scheduler
scheduler = lr_scheduler.ReduceLROnPlateau(optimizer, 'min', verbose=True)
```

Val helper function

```
# Validation helper

def validate_phase(val_dl,best_acc,best_wts):
    # Put the model in eval mode
    model.eval()
    losses = []
    accuracies = []
    epoch_start = time.time()
    # Think this helps....
    with torch.no_grad():
      for i, batch in enumerate(val_dl):
          # print(batch)
          inputs = batch['X'].to(device).type(torch.cuda.FloatTensor)
          labels = batch['y'].to(device).type(torch.cuda.FloatTensor).unsqueeze(1)

          output = model(inputs)            # 2. Run the model
          # print("output shape:",output.shape)
          # print("output:",output)

          loss = criterion(output, labels) # 3. Calculate loss
          losses.append(loss.item())
```

```
        losses.append(loss.item())

        # Make predictions
        preds = output.detach().clone()
        # print(preds)
        preds[preds >= 0.5] = 1
        preds[preds < 0.5 ] = 0
        # print("preds shape: ",preds.shape)
        # print("predictions:",preds)

        # Convert target and predictions to numpy
        labels_np = labels.cpu().numpy()
        preds_np = preds.cpu().numpy()

        # 4. Calculate accuracy
        # This needs to be by batch
        acc_sum = (preds_np == labels_np).sum(0)
        # print(acc_sum)
        acc = acc_sum / preds_np.shape[0]
        accuracies.append(np.mean(acc))

        # print('[VAL] Loss: {:.4f} Acc: {:.4f}'.format(loss.item(), np.mean(acc)))
        # if i == 0:
        #   break


      # epoch_loss = np.sqrt(sum(losses) / len(losses))
      epoch_loss = np.mean(losses)
      epoch_acc = np.mean(accuracies)
      epoch_time = time.time() - epoch_start
      # deep copy the model
      if epoch_acc > best_acc:
        best_acc = epoch_acc
        best_wts = copy.deepcopy(model.state_dict())
        # save
        MODEL_PATH = '/content/drive/My Drive/Colab Notebooks/Machine Learning 2020/old-bail
        torch.save(model.state_dict(), MODEL_PATH)

      print("[VAL] Epoch: {} Loss: {} Acc: {} Time: {:.0f}:{:.0f}".format(epoch+1, epoch_loss,
                                                                  epoch_acc,
                                                                  epoch_time // 60,
                                                                  epoch_time % 60))
    return epoch_loss, epoch_acc, best_acc, best_wts

# epoch = 0
# best_acc = 100
# best_wts = None
# loss, acc, best_acc, best_wts = validate_phase(val_loader,best_acc,best_wts)
# print(loss,acc,best_acc,best_wts)
```

Train helper function

```
def train_phase(train_dl):
    model.train()
```

```
model.train()
losses = []
accuracies = []
epoch_start = time.time()
with torch.enable_grad(): # resets grads
  for i, batch in enumerate(train_dl):
      inputs = batch['X'].to(device).type(torch.cuda.FloatTensor)
      labels = batch['y'].to(device).type(torch.cuda.FloatTensor).unsqueeze(1)

      optimizer.zero_grad()              # 1. Zero the parameter gradients
      output = model(inputs)            # 2. Run the model

      loss = criterion(output, labels) # 3. Calculate loss
      losses.append(loss.item())


      loss.backward()                   # 4. Backward propagate the loss
      optimizer.step()                  # 5. Optimize the network

      # Make predictions
      preds = output.detach().clone()
      # print(preds)
      preds[preds >= 0.5] = 1
      preds[preds < 0.5 ] = 0

      # Convert target and predictions to numpy
      labels_np = labels.cpu().numpy()
      preds_np = preds.cpu().numpy()

      # 4. Calculate accuracy
      # This needs to be by batch
      acc_sum = (preds_np == labels_np).sum(0)
      # print(acc_sum)
      acc = acc_sum / preds_np.shape[0]
      accuracies.append(np.mean(acc))

      # print('[TRN] Loss: {:.4f} Acc: {:.4f}'.format(loss.item(), np.mean(acc)))
      if i == 0:
        break

# save
# MODEL_PATH = '/content/drive/My Drive/Colab Notebooks/Deep Learning 2020/project/saved_m
# MODEL_PATH_WHOLE = '/content/drive/My Drive/Colab Notebooks/Deep Learning 2020/project/s
# torch.save(model.state_dict(), MODEL_PATH)
# torch.save({
#         'epoch': epoch+1,
#         'model_state_dict': model.state_dict(),
#         'optimizer_state_dict': optimizer.state_dict()
#         }, MODEL_PATH_WHOLE)

epoch_loss = np.mean(losses)
epoch_acc = np.mean(accuracies)
epoch_time = time.time() - epoch_start
print("[TRN] Epoch: {} Loss: {} Acc: {} Time: {:.0f}:{:.0f}".format(epoch+1,
                                                              epoch_loss,
                                                              epoch_acc,
```

```
                                                                 epoch_time // 60,
                                                                 epoch_time % 60))
    return epoch_loss, epoch_acc

# epoch = 0
# loss, acc = train_phase(train_loader)
# print(loss,acc)
```

Main training loop

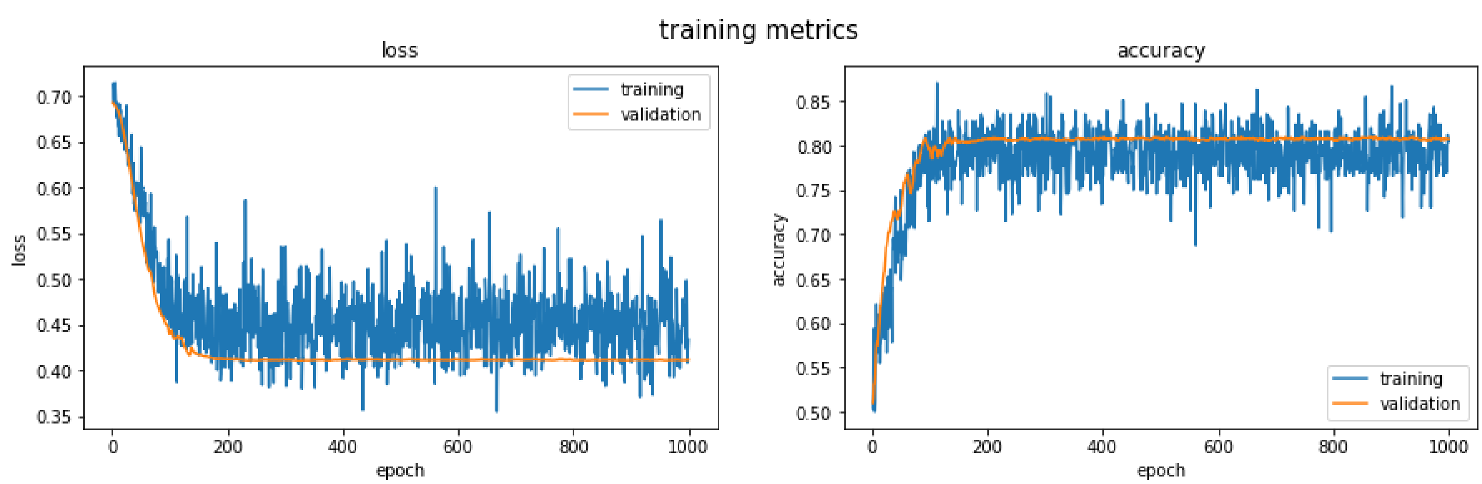
```
# Load a previous checkpoint to resume training if necessary
# PATH = '/content/drive/My Drive/Colab Notebooks/Deep Learning 2020/project/saved_models/chec
# model.load_state_dict(torch.load(PATH))

# Init best model weights and accuracy
best_wts = None
best_acc = 0.85
epochs = 1000

train_losses = []
train_accs = []

val_losses = []
val_accs = []

for epoch in tqdm(range(epochs)):
    # Train and val
    train_loss, train_acc = train_phase(train_loader)
    val_loss, val_acc, best_acc, best_wts = validate_phase(val_loader,best_acc,best_wts)

    # Adjust learning rate if needs be
    scheduler.step(val_loss)

    # store train values
    train_losses.append(train_loss)
    train_accs.append(train_acc)

    # store val values
    val_losses.append(val_loss)
    val_accs.append(val_acc)

    print(" \n")



# load best model weights
# best_model = model.load_state_dict(best_wts)
# save whole model: https://pytorch.org/tutorials/beginner/saving_loading_models.html
# MODEL_PATH = '/content/drive/My Drive/Colab Notebooks/Deep Learning 2020/project/saved_model
# torch.save(best_wts, MODEL_PATH)
```

47% 473/1000 [03:48<04:18, 2.04it/s]

```
[TRN] Epoch: 1 Loss: 0.7683291435241699 Acc: 0.53125 Time: 0:0
[VAL] Epoch: 1 Loss: 0.6944640609953139 Acc: 0.4888313050055005 Time: 0:0


[TRN] Epoch: 2 Loss: 0.8029769659042358 Acc: 0.5 Time: 0:0
[VAL] Epoch: 2 Loss: 0.6937013665835062 Acc: 0.4888313050055005 Time: 0:0


[TRN] Epoch: 3 Loss: 0.6818060874938965 Acc: 0.57421875 Time: 0:0
[VAL] Epoch: 3 Loss: 0.6928331984413995 Acc: 0.4888313050055005 Time: 0:0


[TRN] Epoch: 4 Loss: 0.7222598791122437 Acc: 0.55859375 Time: 0:0
[VAL] Epoch: 4 Loss: 0.691793421904246 Acc: 0.4888313050055005 Time: 0:0


[TRN] Epoch: 5 Loss: 0.6536573171615601 Acc: 0.6015625 Time: 0:0
[VAL] Epoch: 5 Loss: 0.690633601612515 Acc: 0.4888313050055005 Time: 0:0


[TRN] Epoch: 6 Loss: 0.6585459113121033 Acc: 0.6328125 Time: 0:0
[VAL] Epoch: 6 Loss: 0.689545108212365 Acc: 0.4888313050055005 Time: 0:0


[TRN] Epoch: 7 Loss: 0.6342058777809143 Acc: 0.65625 Time: 0:0
[VAL] Epoch: 7 Loss: 0.6885919637150235 Acc: 0.5331623006050604 Time: 0:0


[TRN] Epoch: 8 Loss: 0.5619655847549438 Acc: 0.7109375 Time: 0:0
[VAL] Epoch: 8 Loss: 0.6875632272826301 Acc: 0.7904677186468647 Time: 0:0


[TRN] Epoch: 9 Loss: 0.6221763491630554 Acc: 0.64453125 Time: 0:0
[VAL] Epoch: 9 Loss: 0.6865809758504232 Acc: 0.7921178836633663 Time: 0:0


[TRN] Epoch: 10 Loss: 0.5977980494499207 Acc: 0.703125 Time: 0:0
[VAL] Epoch: 10 Loss: 0.6856267319785224 Acc: 0.7963421342134214 Time: 0:0


[TRN] Epoch: 11 Loss: 0.5635846853256226 Acc: 0.73828125 Time: 0:0
[VAL] Epoch: 11 Loss: 0.6844958265622457 Acc: 0.7873435781078109 Time: 0:0


[TRN] Epoch: 12 Loss: 0.5723814964294434 Acc: 0.67578125 Time: 0:0
[VAL] Epoch: 12 Loss: 0.6832079158888923 Acc: 0.7692003575357536 Time: 0:0


[TRN] Epoch: 13 Loss: 0.5901724696159363 Acc: 0.7109375 Time: 0:0
[VAL] Epoch: 13 Loss: 0.6817624635166593 Acc: 0.7537472497249724 Time: 0:0


[TRN] Epoch: 14 Loss: 0.5613524913787842 Acc: 0.7734375 Time: 0:0
[VAL] Epoch: 14 Loss: 0.6805519726541307 Acc: 0.6917930074257426 Time: 0:0
```

Plot Loss and acc

```
epochs_ = range(1,epochs+1)

# Displaying images and targets side by side
fig, axarr = plt.subplots(1, 2,figsize=(15,4))
fig.suptitle('training metrics',fontsize=15)
axarr[0].plot(epochs_,train_losses,label='training')
axarr[0].plot(epochs_,val_losses,label='validation')
axarr[0].set_xlabel("epoch")
axarr[0].set_ylabel("loss")
axarr[0].legend()
axarr[0].set_title("loss")
axarr[1].plot(epochs_,train_accs,label='training')
axarr[1].plot(epochs_,val_accs,label='validation')
axarr[1].set_xlabel("epoch")
axarr[1].set_ylabel("accuracy")
axarr[1].legend()
axarr[1].set_title("accuracy")


plt.show()
```



Load top 5 performers and use them as an ensemble

```
[VAL] Epoch: 27 Loss: 0.656152394082811 Acc: 0.699373452970297 Time: 0:0
```

```
# Models in descending order of val acccuaracy
PATH1 = '/content/drive/My Drive/Colab Notebooks/Machine Learning 2020/old-bailey-decisions/py
PATH2 = '/content/drive/My Drive/Colab Notebooks/Machine Learning 2020/old-bailey-decisions/py
PATH3 = '/content/drive/My Drive/Colab Notebooks/Machine Learning 2020/old-bailey-decisions/py
PATH4 = '/content/drive/My Drive/Colab Notebooks/Machine Learning 2020/old-bailey-decisions/py
PATH5 = '/content/drive/My Drive/Colab Notebooks/Machine Learning 2020/old-bailey-decisions/py

def TwoLayerNet():
  model = nn.Sequential(
    nn.Linear(in_features=10084,out_features=1000),
    nn.BatchNorm1d(1000),
    nn.ReLU(),
    nn.Dropout(0.85),
    nn.Linear(1000,100),
```

```
    nn.BatchNorm1d(100),
    nn.ReLU(),
    nn.Dropout(0.8),
    nn.Linear(100,1),
    nn.Sigmoid()
  )
  return model


# Load models from path
model_1 = TwoLayerNet()
model_2 = TwoLayerNet()
model_3 = TwoLayerNet()
model_4 = TwoLayerNet()
model_5 = TwoLayerNet()

def LoadState(model,PATH):
  model.load_state_dict(torch.load(PATH))
  model.eval()

LoadState(model_1,PATH1)
LoadState(model_2,PATH2)
LoadState(model_3,PATH3)
LoadState(model_4,PATH4)
LoadState(model_5,PATH5)
```

Now, run each model on the test set and combine predictions, taking majority vote as the label

```
def get_predictions(model,data_loader):
  accuracies = []
  predictions = []
  for i,batch in enumerate(tqdm(data_loader)):
    inputs = batch['X'].to(device).type(torch.cuda.FloatTensor)
    labels = batch['y'].cpu().numpy()
    model.to(device)
    model.eval()
    with torch.no_grad():
      output = model(inputs)
      # print(output)

      # Make predictions
      preds = output.detach().clone()
      # print(preds)
      preds[preds >= 0.5] = 1
      preds[preds < 0.5 ] = 0
      # print("preds shape: ",preds.shape)
      # print("predictions:",preds)
      # print("label:",labels)
      predictions.append(preds.squeeze().cpu().numpy())

      # Convert target and predictions to numpy
      labels_np = labels
      preds_np = preds.cpu().numpy()
```

```
      # 4. Calculate accuracy
      # This needs to be by batch
      acc_sum = (preds_np == labels_np).sum(0)
      # print(acc_sum)
      acc = acc_sum / preds_np.shape[0]
      accuracies.append(np.mean(acc))
      # print("accs:",np.mean(acc))
      # if i == 6:
      #   break
  print(np.mean(accuracies))
  return np.array(predictions)


m1_preds = get_predictions(model_1,val_loader)
m2_preds = get_predictions(model_2,val_loader)
m3_preds = get_predictions(model_3,val_loader)
m4_preds = get_predictions(model_4,val_loader)
m5_preds = get_predictions(model_5,val_loader)
```

100% 2250/2250 [00:13<00:00, 164.18it/s]

```
0.8506666666666667
```

100% 2250/2250 [01:43<00:00, 21.70it/s]

```
0.8493333333333334
```

100% 2250/2250 [00:06<00:00, 343.31it/s]

```
0.8488888888888889
```

100% 2250/2250 [01:36<00:00, 23.29it/s]

```
0.848
```

100% 2250/2250 [01:06<00:00, 33.80it/s]

```
0.8471111111111111
```

Load data into numpy arrays for ensemble + random forest evaluation

```
# Load data for random forest + NN ensemble evaluation
def load_data(path):
  data = pd.read_csv(path).to_numpy()
  X = data[:,1:]
  y = data[:,0]
  y[y == -1] = 0
  return X,y

%time X,y = load_data(TRAINING_PATH_TF)
%time X_val, y_val = load_data(TESTING_PATH_TF)
%time Xm,ym = load_data(TRAINING_PATH)
%time Xm_val, ym_val = load_data(TESTING_PATH)
```

```
CPU times: user 58.4 s, sys: 2.42 s, total: 1min
Wall time: 1min 4s
CPU times: user 7.82 s, sys: 166 ms, total: 7.99 s
Wall time: 14.5 s
CPU times: user 55.3 ms, sys: 15 ms, total: 70.3 ms
Wall time: 5 s
CPU times: user 12.8 ms, sys: 36 µs, total: 12.8 ms
Wall time: 1.22 s

[TRN] Epoch: 65 Loss: 0.41450950503349304 Acc: 0.84375 Time: 0:0
```

Combine these preds into 1 and evaluate accuracy

```
preds = m1_preds + m2_preds + m3_preds + m4_preds + m5_preds
for i,pred in enumerate(preds):
  if pred >= 3:
    preds[i] = 1
  else:
    preds[i] = 0

print(m1_preds[0:10])
print(m2_preds[0:10])
print(m3_preds[0:10])
print(m4_preds[0:10])
print(m5_preds[0:10])
print(preds[0:10])

# Get accuracy
equal = np.equal(preds,y_val)
acc = np.sum(equal)/y_val.shape[0]
print("ensemble test acc: ",acc)
```

```
[0. 1. 0. 0. 0. 0. 0. 0. 1. 0.]
[0. 1. 0. 0. 0. 0. 0. 0. 1. 0.]
[0. 1. 0. 0. 0. 0. 0. 0. 1. 0.]
[0. 1. 0. 0. 0. 0. 0. 0. 1. 0.]
[0. 1. 0. 0. 0. 0. 0. 0. 1. 0.]
[0. 1. 0. 0. 0. 0. 0. 0. 1. 0.]
ensemble test acc:  0.8493333333333334

[VAL] Epoch: 73 Loss: 0.4113531708717346 Acc: 0.8132992986798679 Time: 0:0
```

Now, run on eval set and return. Additionally, return the eval set of the best classifier m1.

```
[TRN] Epoch: 74 Loss: 0.40180763602256775 Acc: 0.828125 Time: 0:0
```

```
# Load eval data
%time X_eval, y_eval = load_data(EVAL_PATH_TF)
```

```
CPU times: user 19.1 s, sys: 1.31 s, total: 20.4 s
Wall time: 20.6 s
```

```
# eval ids
def load_ids(file_path):
  with open(file_path) as f:
    raw_data = [int(line.split()[0]) for line in f]
  # print(raw_data)
  return raw_data
```

```
eval_ids = np.reshape(np.array(load_ids(EVAL_IDS),dtype=np.int32),(X_eval.shape[0],1))
# print(eval_ids)

m1_preds = get_predictions(model_1,eval_loader)
m2_preds = get_predictions(model_2,eval_loader)
m3_preds = get_predictions(model_3,eval_loader)
m4_preds = get_predictions(model_4,eval_loader)
m5_preds = get_predictions(model_5,eval_loader)

preds = m1_preds + m2_preds + m3_preds + m4_preds + m5_preds
for i,pred in enumerate(preds):
  if pred >= 3:
    preds[i] = 1
  else:
    preds[i] = 0

predictions = np.reshape(preds,(X_eval.shape[0],1))
print(predictions.shape)
print(predictions)
eval_out = np.hstack((eval_ids,predictions))
print(eval_out.shape)
print(eval_out)
eval_df = pd.DataFrame(data = eval_out,index = None,columns=['example_id','label'])
save_to_path = '/content/drive/My Drive/Colab Notebooks/Machine Learning 2020/old-bailey-decis
eval_df.to_csv(path_or_buf=save_to_path,index=False)
```

100%   5250/5250 [00:12<00:00, 437.00it/s]

0.5457142857142857

Now, run the predictions using only my best model.

```
predictions = np.reshape(m1_preds,(X_eval.shape[0],1))
# print(predictions.shape)
# print(predictions)
eval_out = np.hstack((eval_ids,predictions))
# print(eval_out.shape)
# print(eval_out)
eval_df = pd.DataFrame(data = eval_out,index = None,columns=['example_id','label'])
save_to_path = '/content/drive/My Drive/Colab Notebooks/Machine Learning 2020/old-bailey-decis
eval_df.to_csv(path_or_buf=save_to_path,index=False)
```

Feature extractor

Let's adapt my model to spit out the second to last layer

```
# For resnet
feat_ext = torch.nn.Sequential(*list(model_1.children())[:-5]) #Using model_1 here
print(feat_ext)

# gives me a 100 element feature vector
# Can transform my feature space this way. May be good for
# random forest?
feat_size = 100
X_train = np.empty(shape=(len(train_data),feat_size))
y_train = np.empty(shape=(len(train_data),1))
X_test = np.empty(shape=(len(val_data),feat_size))
y_test = np.empty(shape=(len(val_data),1))
X_eval = np.empty(shape=(len(eval_data),feat_size))
y_eval = np.empty(shape=(len(eval_data),1))

# Loop through datasets to extract feats
def feat_extractor(data_loader,X,y,feat_ext):
  model = feat_ext
  model.to(device)
  model.eval()
  for i,batch in enumerate(tqdm(data_loader)):
    inputs = batch['X'].to(device).type(torch.cuda.FloatTensor)
    labels = batch['y'].cpu().numpy()
    with torch.no_grad():
      output = model(inputs)
      feat_vec = output.squeeze().cpu().numpy()
      # Store in arrays
      X[i,:] = feat_vec
      y[i,:] = labels
```

```
feat_extractor(train_loader,X_train,y_train,feat_ext)
feat_extractor(val_loader,X_test,y_test,feat_ext)
feat_extractor(eval_loader,X_eval,y_eval,feat_ext)
```

```
Sequential(
  (0): Linear(in_features=10084, out_features=1000, bias=True)
  (1): BatchNorm1d(1000, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (2): ReLU()
  (3): Dropout(p=0.85, inplace=False)
  (4): Linear(in_features=1000, out_features=100, bias=True)
)
```

100% 17500/17500 [00:12<00:00, 1415.37it/s]

100% 2250/2250 [01:05<00:00, 34.23it/s]

100% 5250/5250 [01:04<00:00, 81.58it/s]

Examine feature vectors + save them

```
[VAL] Epoch: 115 Loss: 0.3590848412778642 Acc: 0.8295903809130913 Time: 0:0
```

```
outfile1 = '/content/drive/My Drive/Colab Notebooks/Machine Learning 2020/old-bailey-decisions
outfile2 = '/content/drive/My Drive/Colab Notebooks/Machine Learning 2020/old-bailey-decisions
outfile3 = '/content/drive/My Drive/Colab Notebooks/Machine Learning 2020/old-bailey-decisions
outfile4 = '/content/drive/My Drive/Colab Notebooks/Machine Learning 2020/old-bailey-decisions
outfile5 = '/content/drive/My Drive/Colab Notebooks/Machine Learning 2020/old-bailey-decisions
outfile6 = '/content/drive/My Drive/Colab Notebooks/Machine Learning 2020/old-bailey-decisions
np.save(outfile1, X_train)
np.save(outfile2, y_train)
np.save(outfile3, X_test)
np.save(outfile4, y_test)
np.save(outfile5, X_eval)
np.save(outfile6, y_eval)
```

```
[TRN] Epoch: 119 Loss: 0.34334439039230347 Acc: 0.875 Time: 0:0
```

Let's try random forest as well.

Maybe I can use the second to last layer of my neural net as my input features to random forest.

Fit feature vec outputs and evaluate my random forest.

https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestClassifier.html

```
for i in range(5,30):
  clf = RandomForestClassifier(max_depth=i+1, random_state=0, criterion='gini')
  %time clf.fit(X_train, np.ravel(y_train))
  score = clf.score(X_test,np.ravel(y_test))
  print(i,':',score)
```

```
CPU times: user 8.13 s, sys: 7.53 ms, total: 8.14 s
```

```
Wall time: 8.15 s
5 : 0.8435555555555555
CPU times: user 9.15 s, sys: 8.49 ms, total: 9.16 s
Wall time: 9.15 s
6 : 0.8444444444444444
CPU times: user 10.1 s, sys: 2.55 ms, total: 10.1 s
Wall time: 10.1 s
7 : 0.8422222222222222
CPU times: user 11.1 s, sys: 6.49 ms, total: 11.1 s
Wall time: 11.1 s
8 : 0.8435555555555555
CPU times: user 12.2 s, sys: 3.65 ms, total: 12.2 s
Wall time: 12.2 s
9 : 0.8408888888888889
CPU times: user 12.9 s, sys: 5.55 ms, total: 12.9 s
Wall time: 12.9 s
10 : 0.8431111111111111
CPU times: user 13.8 s, sys: 2.28 ms, total: 13.8 s
Wall time: 13.8 s
11 : 0.8448888888888889
CPU times: user 14.1 s, sys: 5.38 ms, total: 14.1 s
Wall time: 14.1 s
12 : 0.8426666666666667
CPU times: user 14.6 s, sys: 6.56 ms, total: 14.6 s
Wall time: 14.6 s
13 : 0.8457777777777777
CPU times: user 15.2 s, sys: 10.4 ms, total: 15.2 s
Wall time: 15.2 s
14 : 0.8448888888888889
CPU times: user 15.3 s, sys: 9.39 ms, total: 15.3 s
Wall time: 15.3 s
15 : 0.8426666666666667
CPU times: user 15.7 s, sys: 5.57 ms, total: 15.7 s
Wall time: 15.7 s
16 : 0.8431111111111111
CPU times: user 15.9 s, sys: 8.42 ms, total: 15.9 s
Wall time: 15.9 s
17 : 0.8448888888888889
CPU times: user 16.1 s, sys: 5.52 ms, total: 16.1 s
Wall time: 16.1 s
18 : 0.8431111111111111
CPU times: user 16.3 s, sys: 7.59 ms, total: 16.3 s
Wall time: 16.3 s
19 : 0.8448888888888889
CPU times: user 16.4 s, sys: 4.56 ms, total: 16.5 s
Wall time: 16.4 s
20 : 0.844
CPU times: user 16.6 s, sys: 3.53 ms, total: 16.6 s
Wall time: 16.6 s
21 : 0.8404444444444444
CPU times: user 17 s, sys: 11.5 ms, total: 17 s
Wall time: 17 s
22 : 0.8435555555555555
CPU times: user 16.4 s, sys: 5.58 ms, total: 16.5 s
Wall time: 16.4 s
23 : 0.8457777777777777
CPU times: user 16.8 s, sys: 6.5 ms, total: 16.8 s
Wall time: 16.8 s
[TRN] Epoch: 139 Loss: 0.3342564931869507 Acc: 0.859375 Time: 0:0
```

Run my random forest on eval set, using a depth of 12.

```
clf = RandomForestClassifier(max_depth=12, random_state=0, criterion='gini')
%time clf.fit(X_train, np.ravel(y_train))
```

```
CPU times: user 13.8 s, sys: 5.78 ms, total: 13.8 s
Wall time: 13.8 s
RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight=None,
                       criterion='gini', max_depth=12, max_features='auto',
                       max_leaf_nodes=None, max_samples=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=100,
                       n_jobs=None, oob_score=False, random_state=0, verbose=0,
                       warm_start=False)
```

```
predictions = clf.predict(X_eval)

# eval ids
def load_ids(file_path):
  with open(file_path) as f:
    raw_data = [int(line.split()[0]) for line in f]
  # print(raw_data)
  return raw_data

eval_ids = np.reshape(np.array(load_ids(EVAL_IDS),dtype=np.int32),(X_eval.shape[0],1))


print(predictions)
predictions = np.reshape(predictions,(X_eval.shape[0],1))
# print(predictions.shape)
# print(predictions)
eval_out = np.hstack((eval_ids,predictions))
# print(eval_out.shape)
# print(eval_out)
eval_df = pd.DataFrame(data = eval_out,index = None,columns=['example_id','label'])
save_to_path = '/content/drive/My Drive/Colab Notebooks/Machine Learning 2020/old-bailey-decis
eval_df.to_csv(path_or_buf=save_to_path,index=False)
```

```
[1. 0. 0. ... 1. 0. 0.]
```

Random forest eval on just misc attrs

```
for i in range(5,30):
  clf = RandomForestClassifier(max_depth=i+1, random_state=0, criterion='gini')
  %time clf.fit(Xm, ym)
  score = clf.score(Xm_val,ym_val)
  print(i,':',score)
```

```
CPU times: user 552 ms, sys: 0 ns, total: 552 ms
```

```
Wall time: 557 ms
5 : 0.7928888888888889
CPU times: user 579 ms, sys: 0 ns, total: 579 ms
Wall time: 579 ms
6 : 0.7937777777777778
CPU times: user 639 ms, sys: 0 ns, total: 639 ms
Wall time: 639 ms
7 : 0.7915555555555556
CPU times: user 678 ms, sys: 0 ns, total: 678 ms
Wall time: 677 ms
8 : 0.7946666666666666
CPU times: user 747 ms, sys: 913 µs, total: 748 ms
Wall time: 747 ms
9 : 0.7951111111111111
CPU times: user 743 ms, sys: 0 ns, total: 743 ms
Wall time: 741 ms
10 : 0.7955555555555556
CPU times: user 832 ms, sys: 0 ns, total: 832 ms
Wall time: 830 ms
11 : 0.7946666666666666
CPU times: user 877 ms, sys: 888 µs, total: 877 ms
Wall time: 877 ms
12 : 0.7946666666666666
CPU times: user 900 ms, sys: 948 µs, total: 901 ms
Wall time: 900 ms
13 : 0.7928888888888889
CPU times: user 927 ms, sys: 889 µs, total: 928 ms
Wall time: 927 ms
14 : 0.7933333333333333
CPU times: user 948 ms, sys: 947 µs, total: 949 ms
Wall time: 948 ms
15 : 0.7911111111111111
CPU times: user 1.01 s, sys: 884 µs, total: 1.01 s
Wall time: 1.01 s
16 : 0.792
CPU times: user 1.01 s, sys: 875 µs, total: 1.01 s
Wall time: 1.01 s
17 : 0.7928888888888889
CPU times: user 1.06 s, sys: 0 ns, total: 1.06 s
Wall time: 1.06 s
18 : 0.7906666666666666
CPU times: user 1.11 s, sys: 829 µs, total: 1.11 s
Wall time: 1.11 s
19 : 0.7902222222222223
CPU times: user 1.11 s, sys: 0 ns, total: 1.11 s
Wall time: 1.11 s
20 : 0.7897777777777778
CPU times: user 1.11 s, sys: 0 ns, total: 1.11 s
Wall time: 1.11 s
21 : 0.7897777777777778
CPU times: user 1.14 s, sys: 2.9 ms, total: 1.15 s
Wall time: 1.15 s
22 : 0.7897777777777778
CPU times: user 1.13 s, sys: 1.9 ms, total: 1.13 s
Wall time: 1.13 s
23 : 0.7888888888888889
CPU times: user 1.15 s, sys: 927 µs, total: 1.15 s
Wall time: 1.15 s
```

Scraps

[VAL] Epoch: 171 Loss: 0.34749135706159806 Acc: 0.8389370187018702 Time: 0:0

```
model = None
optimizer = None

################################################################################
# TODO: Rewrite the 2-layer ConvNet with bias from Part III with the           #
# Sequential API.                                                              #
################################################################################
# *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
# class Random_Weight(nn.Module):
#   def __init__(self, *args):
#       super().__init__()
#       self.args = args
#   def forward(self,x):
#       return random_weight(self.args)

# class Zero_Weight(nn.Module):
#   def __init__(self,args):
#     super().__init__()
#     self.args = args
#   def forward(self,x):
#     return zero_weight((self.args,))

model = nn.Sequential(
    nn.Conv2d(3,channel_1,5,padding=2,bias=True),
    # Random_Weight(channel_1,3,5,5),
    # Zero_Weight(channel_1),
    nn.ReLU(),
    nn.Conv2d(channel_1,channel_2,3,padding=1,bias=True),
    # Random_Weight(channel_2,channel_1,3,3),
    # Zero_Weight(channel_2),
    nn.ReLU(),
    Flatten(),
    nn.Linear(channel_2*32*32,10,bias=True),
    # Random_Weight(10,channel_2*32*32),
    # Zero_Weight(10)
)

# loop through now and initialize weights using my functions.. I guess?
# Super unclear how to initialize weight with the sequential API.
# This seems to help: https://www.thetopsites.net/article/52545824.shtml
# def init_weights(m):
#     if type(m) == nn.Linear:
#       # torch.nn.init.xavier_uniform(m.weight)
#       # m.bias.data.fill_(0.01)

# net = nn.Sequential(nn.Linear(2, 2), nn.Linear(2, 2))
# net.apply(init_weights)


# you can use Nesterov momentum in optim.SGD
optimizer = optim.SGD(model.parameters(), lr=learning_rate,
                     momentum=0.9, nesterov=True)
```

[VAL] Epoch: 186 Loss: 0.3493527438905504 Acc: 0.8398050742574257 Time: 0:0

```
# Define my unit block I'll be using
class ConvBlock(nn.Module):
  def __init__(self, channel_1, channel_2,filter,padding):
      super().__init__()
      # batchnorm
      self.bn = nn.BatchNorm2d(channel_1)
      # conv
      self.conv = nn.Conv2d(channel_1,channel_2,filter,padding=padding)
      nn.init.kaiming_normal_(self.conv.weight)

  def forward(self, x):
      z = self.conv(F.relu(self.bn(x)))
      return z

class ConvReluPool(nn.Module):
  def __init__(self,channels,filter=3,padding=1):
    super().__init__()
    self.conv1 = nn.Conv2d(channels[0],channels[1],filter,padding=padding)
    nn.init.kaiming_normal_(self.conv1.weight)
    self.conv2 = nn.Conv2d(channels[1],channels[2],filter,padding=padding)
    nn.init.kaiming_normal_(self.conv2.weight)
    self.pool = nn.MaxPool2d(2,2) # this out will be channels[2]

  def forward(self,x):
    z = self.pool(F.relu(self.conv2(F.relu(self.conv1(x)))))
    return z



channels = [16, 16, 32, 32, 32, 32, 32, 32, 32, 32, 32, 32, 32, 32]
model = nn.Sequential(
    # A few convs to get things going
    nn.Conv2d(3,channels[0],5,padding=2,bias=True),
    nn.ReLU(),
    nn.Conv2d(channels[1],channels[2],5,padding=2,bias=True),

    # Starting into my blocks
    ConvBlock(channels[2],channels[3],5,2),
    ConvBlock(channels[3],channels[4],3,1),
    ConvBlock(channels[4],channels[5],3,1),

    # Lets throw some pooling layers
    ConvReluPool(channels[5:8]),
    ConvReluPool(channels[8:11]),

    # Output layer
    # nn.ReLU(),
    Flatten(),
    nn.Linear(channels[10]*8*8,channels[11],bias=True),
    nn.Linear(channels[11],channels[12]),
    nn.Linear(channels[12],10)
)


# Using adam for my optimizer
```

```
learning_rate = 5e-4
weight_decay = 0
optimizer = optim.Adam(model.parameters(), lr=learning_rate, weight_decay=weight_decay)
```

```
[TRN] Epoch: 203 Loss: 0.33991777896881104 Acc: 0.8515625 Time: 0:0
[VAL] Epoch: 203 Loss: 0.348671641614702 Acc: 0.8406731298129813 Time: 0:0


[TRN] Epoch: 204 Loss: 0.3363172709941864 Acc: 0.84375 Time: 0:0
[VAL] Epoch: 204 Loss: 0.348643163839976 Acc: 0.841107157590759 Time: 0:0


[TRN] Epoch: 205 Loss: 0.2765366733074188 Acc: 0.89453125 Time: 0:0
[VAL] Epoch: 205 Loss: 0.3485773238870833 Acc: 0.841107157590759 Time: 0:0


[TRN] Epoch: 206 Loss: 0.34037360548973083 Acc: 0.85546875 Time: 0:0
[VAL] Epoch: 206 Loss: 0.3487238321039412 Acc: 0.8398050742574257 Time: 0:0


[TRN] Epoch: 207 Loss: 0.32658854126930237 Acc: 0.86328125 Time: 0:0
[VAL] Epoch: 207 Loss: 0.34873322976960075 Acc: 0.841107157590759 Time: 0:0


[TRN] Epoch: 208 Loss: 0.279549241065979 Acc: 0.890625 Time: 0:0
[VAL] Epoch: 208 Loss: 0.3486458990308974 Acc: 0.8406731298129813 Time: 0:0
```