In [11]:
```
# pip install jovian
```

- Reference: https://pytorch.org/tutorials/beginner/transfer_learning_tutorial.html#load-data

In [8]:
```
# module loading
from __future__ import print_function, division

import torch
import torch.nn as nn
import torch.optim as optim
from torch.optim import lr_scheduler
import torch.backends.cudnn as cudnn
import numpy as np
import pandas as pd
import torchvision
from torchvision import datasets, models, transforms
import matplotlib.pyplot as plt
import seaborn as sns
import time
import os
import copy

cudnn.benchmark = True
plt.ion()   # interactive mode
```

Load Data

- Reference: https://pytorch.org/tutorials/beginner/transfer_learning_tutorial.html#load-data

In [3]:
```
# Data augmentation and normalization for training set; for validation set, we only do normalization
data_transforms = {
    'train': transforms.Compose([
        transforms.RandomResizedCrop(224),
        transforms.RandomHorizontalFlip(),
        transforms.ToTensor(),
        transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])
    ]),
    'val': transforms.Compose([
        transforms.Resize(256),
        transforms.CenterCrop(224),
        transforms.ToTensor(),
        transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])
    ]),
    'test': transforms.Compose([
        transforms.Resize(256),
        transforms.CenterCrop(224),
        transforms.ToTensor(),
        transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])
    ]),
}

data_dir = '/content/drive/MyDrive/test colab/Fish'

image_datasets = {x: datasets.ImageFolder(os.path.join(data_dir, x),data_transforms[x])
                  for x in ['train', 'val']}

dataloaders = {x: torch.utils.data.DataLoader(image_datasets[x], batch_size=4, shuffle=True, num_workers=4)
              for x in ['train', 'val']}

dataset_sizes = {x: len(image_datasets[x]) for x in ['train', 'val']}

class_names = image_datasets['train'].classes
```

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

```
/usr/local/lib/python3.7/dist-packages/torch/utils/data/dataloader.py:490: UserWarning: This DataLoader will create 4 worker processes in total. Our suggested max number
of worker in current system is 2, which is smaller than what this DataLoader is going to create. Please be aware that excessive worker creation might get DataLoader runni
ng slow or even freeze, lower the worker number to avoid potential slowness/freeze if necessary.
  cpuset_checked))
```

In [4]:
```
class_names
```

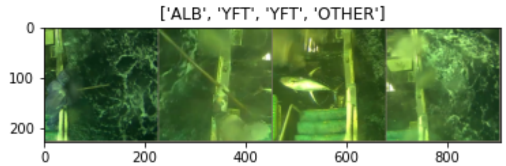
Out[4]:
```
['ALB', 'NoF', 'OTHER', 'YFT']
```

Visualize images

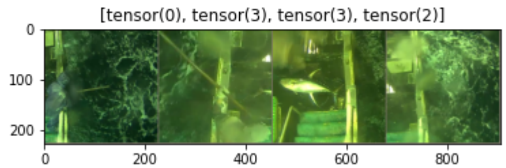
- Reference: https://pytorch.org/tutorials/beginner/transfer_learning_tutorial.html#load-data

In [5]:
```
def imshow(inp, title=None):
    inp = inp.numpy().transpose((1, 2, 0))
    mean = np.array([0.485, 0.456, 0.406])
    std = np.array([0.229, 0.224, 0.225])
    inp = std * inp + mean
    inp = np.clip(inp, 0, 1)
    plt.imshow(inp)
    if title is not None:
        plt.title(title)
    plt.pause(0.001)

# Get a batch of training data
inputs, classes = next(iter(dataloaders['train']))

# Make a grid from batch
out = torchvision.utils.make_grid(inputs)

imshow(out, title=[class_names[x] for x in classes])
```

```
/usr/local/lib/python3.7/dist-packages/torch/utils/data/dataloader.py:490: UserWarning: This DataLoader will create 4 worker processes in total. Our suggested max number
of worker in current system is 2, which is smaller than what this DataLoader is going to create. Please be aware that excessive worker creation might get DataLoader runni
ng slow or even freeze, lower the worker number to avoid potential slowness/freeze if necessary.
  cpuset_checked))
```



In [6]:
```
imshow(out, title=[x for x in classes])
```



Training model

- Reference: https://pytorch.org/tutorials/beginner/transfer_learning_tutorial.html#load-data

In [7]:
```
def train_model(model, criterion, optimizer, scheduler, num_epochs=25):
```

```
    train_losses = []
    val_losses = []

    since = time.time()

    best_model_wts = copy.deepcopy(model.state_dict())
    best_acc = 0.0
    best_epoch = 0

    for epoch in range(num_epochs):
        print(f'Epoch {epoch}/{num_epochs - 1}')
        print('-' * 10)

        # Each epoch has a training and validation phase
        for phase in ['train', 'val']:
            if phase == 'train':
                #scheduler.step()
                model.train()  # Set model to training mode
            else:
                model.eval()   # Set model to evaluate mode

            running_loss = 0.0
            running_corrects = 0

            # Iterate over data.
            for inputs, labels in dataloaders[phase]:
                inputs = inputs.to(device)
                labels = labels.to(device)

                # zero the parameter gradients
                optimizer.zero_grad()

                # forward
                # track history if only in train
                with torch.set_grad_enabled(phase == 'train'):
                    outputs = model(inputs)
                    _, preds = torch.max(outputs, 1)
                    loss = criterion(outputs, labels)

                    # backward + optimize only if in training phase
                    if phase == 'train':
                        loss.backward()
                        optimizer.step()

                # statistics
                running_loss += loss.item() * inputs.size(0)
                running_corrects += torch.sum(preds == labels.data)
            if phase == 'train':
                scheduler.step()

            epoch_loss = running_loss / dataset_sizes[phase]
            epoch_acc = running_corrects.double() / dataset_sizes[phase]

            if phase == 'train':
                train_losses.append(epoch_loss)
            else:
                val_losses.append(epoch_loss)

            print(f'{phase} Loss: {epoch_loss:.4f} Acc: {epoch_acc:.4f}')

            # deep copy the model
            if phase == 'val' and epoch_acc > best_acc:
                best_acc = epoch_acc
                best_model_wts = copy.deepcopy(model.state_dict())
                best_epoch = epoch

        print()
```

```
    time_elapsed = time.time() - since
    print(f'Training complete in {time_elapsed // 60:.0f}m {time_elapsed % 60:.0f}s')
    print(f'Best val Acc: {best_acc:4f}')
    print(f'Best val epoch: {best_epoch}')

    # load best model weights
    model.load_state_dict(best_model_wts)
    return model, train_losses, val_losses
```

1.1.1.(a) Initialize a Resnet18 model

(1) Using the pre-trained Resnet18 model as a fixed feature extractor (only fine-tune the fully-connected layer)

- Reference: https://pytorch.org/tutorials/beginner/transfer_learning_tutorial.html#load-data

In [12]:
```
model_FineTuneFC = torchvision.models.resnet18(pretrained=True)
for param in model_FineTuneFC.parameters():
    param.requires_grad = False

# Parameters of newly constructed modules have requires_grad=True by default
num_FineTuneFC_rs = model_FineTuneFC.fc.in_features

model_FineTuneFC.fc = nn.Linear(num_FineTuneFC_rs, 4) # only 4 classes

model_FineTuneFC = model_FineTuneFC.to(device)

criterion = nn.CrossEntropyLoss()

# Observe that only parameters of final layer are being optimized.
optimizer_FineTuneFC = optim.Adam(model_FineTuneFC.fc.parameters(), lr=0.001)

# Decay LR by a factor of 0.1 every 7 epochs
exp_lr_scheduler_FineTuneFC = lr_scheduler.StepLR(optimizer_FineTuneFC, step_size=7, gamma=0.1)
```

(2) Fine-tuning all layers of the pre-trained Resnet18 model

- Reference: https://pytorch.org/tutorials/beginner/transfer_learning_tutorial.html#load-data

In [9]:
```
model_FineTuning_all = models.resnet18(pretrained=True)

num_FineTuning_all_rs = model_FineTuning_all.fc.in_features

model_FineTuning_all.fc = nn.Linear(num_FineTuning_all_rs, 4) # only 4 classes

model_FineTuning_all = model_FineTuning_all.to(device)

criterion = nn.CrossEntropyLoss()

optimizer_FineTuning_all = optim.Adam(model_FineTuning_all.parameters(), lr=0.001)

# Decay LR by a factor of 0.1 every 7 epochs
exp_lr_scheduler_FineTuning_all = lr_scheduler.StepLR(optimizer_FineTuning_all, step_size=7, gamma=0.1)
```

(3) Training a Resnet18 model from scratch.

- Reference: https://pytorch.org/tutorials/beginner/transfer_learning_tutorial.html#load-data

In [10]:
```
model_scratch = models.resnet18(pretrained=False)

num_scratch_rs = model_scratch.fc.in_features
```

```
model_scratch.fc = nn.Linear(num_scratch_rs, 4)

model_scratch = model_scratch.to(device)

criterion = nn.CrossEntropyLoss()

optimizer_scratch = optim.Adam(model_scratch.parameters(), lr=0.001)

# Decay LR by a factor of 0.1 every 7 epochs
exp_lr_scheduler_scratch = lr_scheduler.StepLR(optimizer_scratch, step_size=7, gamma=0.1)
```

1.1.1.(b) Before training, can you speculate how the training will be different between these three approaches? Which way do you think is the most appropriate given this fishing dataset, and why?

- In my opinion, I think the model that only fine-tune the fully-connected layer would have the best performance among these three approaches. The resnet18 were trained with ImageNet database containing 1,000,000+ images so each weight in each layer can accurately capture the image features. If we reset or fine-tune these weights in all layers and re-train the model by our own images, the model will decrease the ability to capture image features accurately. As a result, Fine-tuning only the fully-connected layer is the most appropriate given this fishing dataset.

1.1.2 Model Training/Fine-tuning

In [13]:
```
# Fine-tuning only the fully-connected layer
model_FineTuneFC, train_losses_FineTuneFC, val_losses_FineTuneFC = train_model(model_FineTuneFC, criterion, optimizer_FineTuneFC, exp_lr_scheduler_FineTuneFC, num_epochs=
```

```
Epoch 0/24
----------
/usr/local/lib/python3.7/dist-packages/torch/utils/data/dataloader.py:490: UserWarning: This DataLoader will create 4 worker processes in total. Our suggested max number
of worker in current system is 2, which is smaller than what this DataLoader is going to create. Please be aware that excessive worker creation might get DataLoader runni
ng slow or even freeze, lower the worker number to avoid potential slowness/freeze if necessary.
  cpuset_checked))
train Loss: 1.2757 Acc: 0.4205
val Loss: 1.4029 Acc: 0.4138

Epoch 1/24
----------
train Loss: 1.1749 Acc: 0.4866
val Loss: 0.8604 Acc: 0.6293

Epoch 2/24
----------
train Loss: 1.1251 Acc: 0.4994
val Loss: 0.8226 Acc: 0.6466

Epoch 3/24
----------
train Loss: 1.1103 Acc: 0.5269
val Loss: 0.8175 Acc: 0.6810

Epoch 4/24
----------
train Loss: 1.0633 Acc: 0.5471
val Loss: 0.9205 Acc: 0.6034

Epoch 5/24
----------
train Loss: 1.0760 Acc: 0.5397
val Loss: 0.8477 Acc: 0.6638

Epoch 6/24
----------
train Loss: 1.0678 Acc: 0.5477
val Loss: 0.8128 Acc: 0.6595

Epoch 7/24
----------
train Loss: 1.0100 Acc: 0.5709
```

```
val Loss: 0.7703 Acc: 0.6810

Epoch 8/24
----------
train Loss: 0.9689 Acc: 0.5856
val Loss: 0.7510 Acc: 0.7112

Epoch 9/24
----------
train Loss: 0.9985 Acc: 0.5630
val Loss: 0.7284 Acc: 0.7112

Epoch 10/24
----------
train Loss: 0.9667 Acc: 0.5972
val Loss: 0.7623 Acc: 0.7155

Epoch 11/24
----------
train Loss: 0.9982 Acc: 0.5752
val Loss: 0.7262 Acc: 0.7026

Epoch 12/24
----------
train Loss: 0.9791 Acc: 0.5899
val Loss: 0.7151 Acc: 0.7241

Epoch 13/24
----------
train Loss: 0.9747 Acc: 0.5954
val Loss: 0.7605 Acc: 0.7026

Epoch 14/24
----------
train Loss: 0.9444 Acc: 0.6082
val Loss: 0.7217 Acc: 0.7457

Epoch 15/24
----------
train Loss: 0.9578 Acc: 0.5868
val Loss: 0.7490 Acc: 0.7026

Epoch 16/24
----------
train Loss: 0.9772 Acc: 0.5636
val Loss: 0.7260 Acc: 0.7026

Epoch 17/24
----------
train Loss: 1.0064 Acc: 0.5623
val Loss: 0.7153 Acc: 0.7414

Epoch 18/24
----------
train Loss: 0.9654 Acc: 0.5947
val Loss: 0.7312 Acc: 0.7241

Epoch 19/24
----------
train Loss: 0.9706 Acc: 0.5990
val Loss: 0.7431 Acc: 0.7328

Epoch 20/24
----------
train Loss: 0.9655 Acc: 0.5886
val Loss: 0.7345 Acc: 0.7155

Epoch 21/24
----------
train Loss: 0.9710 Acc: 0.5966
val Loss: 0.7287 Acc: 0.7198
```

```
Epoch 22/24
----------
train Loss: 0.9599 Acc: 0.6137
val Loss: 0.7218 Acc: 0.7629

Epoch 23/24
----------
train Loss: 0.9615 Acc: 0.5905
val Loss: 0.7568 Acc: 0.7069

Epoch 24/24
----------
train Loss: 0.9747 Acc: 0.5996
val Loss: 0.7242 Acc: 0.7112

Training complete in 81m 11s
Best val Acc: 0.762931
Best val epoch: 22
```

In [11]:

```python
# Fine-tuning all layers
model_FineTuning_all, train_losses_FineTuning_all, val_losses_FineTuning_all = train_model(model_FineTuning_all, criterion, optimizer_FineTuning_all, exp_lr_scheduler_Fin
```

```
Epoch 0/24
----------
/usr/local/lib/python3.7/dist-packages/torch/utils/data/dataloader.py:490: UserWarning: This DataLoader will create 4 worker processes in total. Our suggested max number
of worker in current system is 2, which is smaller than what this DataLoader is going to create. Please be aware that excessive worker creation might get DataLoader runni
ng slow or even freeze, lower the worker number to avoid potential slowness/freeze if necessary.
  cpuset_checked))
train Loss: 1.4276 Acc: 0.3380
val Loss: 1.5179 Acc: 0.3405

Epoch 1/24
----------
train Loss: 1.3324 Acc: 0.3851
val Loss: 1.2252 Acc: 0.4698

Epoch 2/24
----------
train Loss: 1.3182 Acc: 0.3839
val Loss: 1.2834 Acc: 0.3922

Epoch 3/24
----------
train Loss: 1.2772 Acc: 0.4114
val Loss: 1.1721 Acc: 0.4828

Epoch 4/24
----------
train Loss: 1.2842 Acc: 0.3851
val Loss: 1.0892 Acc: 0.4871

Epoch 5/24
----------
train Loss: 1.2719 Acc: 0.4224
val Loss: 1.3602 Acc: 0.4914

Epoch 6/24
----------
train Loss: 1.2544 Acc: 0.4279
val Loss: 1.6557 Acc: 0.4009

Epoch 7/24
----------
train Loss: 1.2315 Acc: 0.4352
val Loss: 1.0729 Acc: 0.5216

Epoch 8/24
----------
train Loss: 1.1813 Acc: 0.4713
val Loss: 1.0235 Acc: 0.5603

Epoch 9/24
```

```
----------
train Loss: 1.1493 Acc: 0.4969
val Loss: 1.0161 Acc: 0.5431

Epoch 10/24
----------
train Loss: 1.1270 Acc: 0.4969
val Loss: 1.0784 Acc: 0.5259

Epoch 11/24
----------
train Loss: 1.1431 Acc: 0.4982
val Loss: 0.9482 Acc: 0.5776

Epoch 12/24
----------
train Loss: 1.1131 Acc: 0.5055
val Loss: 0.9886 Acc: 0.5474

Epoch 13/24
----------
train Loss: 1.0940 Acc: 0.5269
val Loss: 1.0000 Acc: 0.5431

Epoch 14/24
----------
train Loss: 1.0758 Acc: 0.5263
val Loss: 0.9637 Acc: 0.5690

Epoch 15/24
----------
train Loss: 1.0719 Acc: 0.5336
val Loss: 0.9224 Acc: 0.5776

Epoch 16/24
----------
train Loss: 1.0635 Acc: 0.5342
val Loss: 0.9549 Acc: 0.5905

Epoch 17/24
----------
train Loss: 1.0664 Acc: 0.5342
val Loss: 0.9455 Acc: 0.5603

Epoch 18/24
----------
train Loss: 1.0927 Acc: 0.5293
val Loss: 0.9163 Acc: 0.6207

Epoch 19/24
----------
train Loss: 1.0707 Acc: 0.5306
val Loss: 0.9399 Acc: 0.5948

Epoch 20/24
----------
train Loss: 1.0606 Acc: 0.5165
val Loss: 0.9455 Acc: 0.6034

Epoch 21/24
----------
train Loss: 1.0518 Acc: 0.5330
val Loss: 0.9268 Acc: 0.5905

Epoch 22/24
----------
train Loss: 1.0572 Acc: 0.5410
val Loss: 0.9526 Acc: 0.6078

Epoch 23/24
----------
train Loss: 1.0792 Acc: 0.5367
```

```
val Loss: 0.9606 Acc: 0.6121

Epoch 24/24
----------
train Loss: 1.0388 Acc: 0.5538
val Loss: 0.9464 Acc: 0.5862

Training complete in 192m 49s
Best val Acc: 0.620690
Best val epoch: 18
```

In [13]:
```
# Training a Resnet18 model from scratch
model_scratch, train_losses_scratch, val_losses_scratch = train_model(model_scratch, criterion, optimizer_scratch, exp_lr_scheduler_scratch, num_epochs=50)
```

```
Epoch 0/49
----------
/usr/local/lib/python3.7/dist-packages/torch/utils/data/dataloader.py:490: UserWarning: This DataLoader will create 4 worker processes in total. Our suggested max number
of worker in current system is 2, which is smaller than what this DataLoader is going to create. Please be aware that excessive worker creation might get DataLoader runni
ng slow or even freeze, lower the worker number to avoid potential slowness/freeze if necessary.
  cpuset_checked))
train Loss: 1.4074 Acc: 0.3710
val Loss: 1.2385 Acc: 0.4397

Epoch 1/49
----------
train Loss: 1.3394 Acc: 0.3753
val Loss: 1.3532 Acc: 0.3276

Epoch 2/49
----------
train Loss: 1.3066 Acc: 0.3949
val Loss: 1.2850 Acc: 0.3879

Epoch 3/49
----------
train Loss: 1.2852 Acc: 0.4077
val Loss: 1.1941 Acc: 0.3879

Epoch 4/49
----------
train Loss: 1.2636 Acc: 0.4242
val Loss: 1.1005 Acc: 0.5043

Epoch 5/49
----------
train Loss: 1.2517 Acc: 0.4169
val Loss: 1.2268 Acc: 0.4095

Epoch 6/49
----------
train Loss: 1.2400 Acc: 0.4444
val Loss: 1.2241 Acc: 0.4569

Epoch 7/49
----------
train Loss: 1.2233 Acc: 0.4554
val Loss: 1.0697 Acc: 0.5129

Epoch 8/49
----------
train Loss: 1.1823 Acc: 0.4847
val Loss: 1.0497 Acc: 0.4828

Epoch 9/49
----------
train Loss: 1.1750 Acc: 0.4780
val Loss: 1.0314 Acc: 0.5129

Epoch 10/49
----------
train Loss: 1.1958 Acc: 0.4700
val Loss: 1.0201 Acc: 0.5129
```

```
Epoch 11/49
----------
train Loss: 1.1537 Acc: 0.4859
val Loss: 1.0002 Acc: 0.5431

Epoch 12/49
----------
train Loss: 1.1668 Acc: 0.4896
val Loss: 1.0130 Acc: 0.5043

Epoch 13/49
----------
train Loss: 1.1370 Acc: 0.5000
val Loss: 0.9523 Acc: 0.5647

Epoch 14/49
----------
train Loss: 1.1351 Acc: 0.4963
val Loss: 0.9574 Acc: 0.5560

Epoch 15/49
----------
train Loss: 1.1107 Acc: 0.5196
val Loss: 0.9334 Acc: 0.5517

Epoch 16/49
----------
train Loss: 1.1195 Acc: 0.5134
val Loss: 0.9313 Acc: 0.5603

Epoch 17/49
----------
train Loss: 1.1116 Acc: 0.5183
val Loss: 0.9496 Acc: 0.5603

Epoch 18/49
----------
train Loss: 1.1063 Acc: 0.5171
val Loss: 0.9381 Acc: 0.5690

Epoch 19/49
----------
train Loss: 1.1081 Acc: 0.5141
val Loss: 0.9285 Acc: 0.5733

Epoch 20/49
----------
train Loss: 1.1048 Acc: 0.5244
val Loss: 0.9266 Acc: 0.5905

Epoch 21/49
----------
train Loss: 1.1013 Acc: 0.5226
val Loss: 0.9382 Acc: 0.5690

Epoch 22/49
----------
train Loss: 1.1092 Acc: 0.5147
val Loss: 0.9331 Acc: 0.5905

Epoch 23/49
----------
train Loss: 1.0990 Acc: 0.5122
val Loss: 0.9260 Acc: 0.5690

Epoch 24/49
----------
train Loss: 1.1056 Acc: 0.5153
val Loss: 0.9401 Acc: 0.5776

Epoch 25/49
```

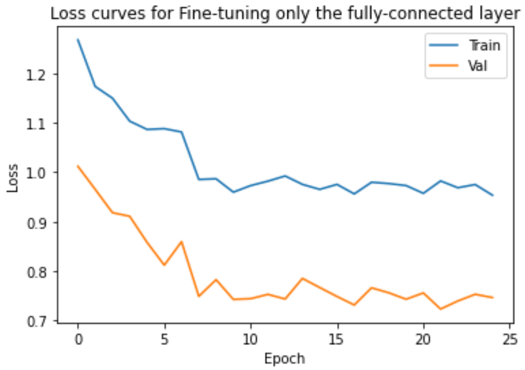
```
----------
train Loss: 1.1118 Acc: 0.5257
val Loss: 0.9240 Acc: 0.5862

Epoch 26/49
----------
train Loss: 1.1047 Acc: 0.5122
val Loss: 0.9409 Acc: 0.5517

Epoch 27/49
----------
train Loss: 1.1027 Acc: 0.5037
val Loss: 0.9243 Acc: 0.5733

Epoch 28/49
----------
train Loss: 1.1066 Acc: 0.5226
val Loss: 0.9431 Acc: 0.5733

Epoch 29/49
----------
train Loss: 1.0943 Acc: 0.5183
val Loss: 0.9339 Acc: 0.5819

Epoch 30/49
----------
train Loss: 1.1082 Acc: 0.5092
val Loss: 0.9313 Acc: 0.5647

Epoch 31/49
----------
train Loss: 1.1089 Acc: 0.5098
val Loss: 0.9410 Acc: 0.5690

Epoch 32/49
----------
train Loss: 1.0894 Acc: 0.5257
val Loss: 0.9331 Acc: 0.5819

Epoch 33/49
----------
train Loss: 1.1093 Acc: 0.5086
val Loss: 0.9237 Acc: 0.5690

Epoch 34/49
----------
train Loss: 1.1015 Acc: 0.5122
val Loss: 0.9226 Acc: 0.5776

Epoch 35/49
----------
train Loss: 1.0832 Acc: 0.5238
val Loss: 0.9293 Acc: 0.5647

Epoch 36/49
----------
train Loss: 1.0965 Acc: 0.5238
val Loss: 0.9305 Acc: 0.5862

Epoch 37/49
----------
train Loss: 1.0982 Acc: 0.5104
val Loss: 0.9219 Acc: 0.5733

Epoch 38/49
----------
train Loss: 1.0958 Acc: 0.5189
val Loss: 0.9464 Acc: 0.5776

Epoch 39/49
----------
train Loss: 1.0913 Acc: 0.5104
```

```
val Loss: 0.9249 Acc: 0.5647

Epoch 40/49
----------
train Loss: 1.1105 Acc: 0.5086
val Loss: 0.9230 Acc: 0.5733

Epoch 41/49
----------
train Loss: 1.1156 Acc: 0.5134
val Loss: 0.9352 Acc: 0.5776

Epoch 42/49
----------
train Loss: 1.1073 Acc: 0.5043
val Loss: 0.9180 Acc: 0.5733

Epoch 43/49
----------
train Loss: 1.1021 Acc: 0.5348
val Loss: 0.9291 Acc: 0.5603

Epoch 44/49
----------
train Loss: 1.0980 Acc: 0.5141
val Loss: 0.9294 Acc: 0.5690

Epoch 45/49
----------
train Loss: 1.1041 Acc: 0.5128
val Loss: 0.9345 Acc: 0.5776

Epoch 46/49
----------
train Loss: 1.1016 Acc: 0.5165
val Loss: 0.9322 Acc: 0.5776

Epoch 47/49
----------
train Loss: 1.1269 Acc: 0.4945
val Loss: 0.9334 Acc: 0.5733

Epoch 48/49
----------
train Loss: 1.0866 Acc: 0.5196
val Loss: 0.9230 Acc: 0.5517

Epoch 49/49
----------
train Loss: 1.1061 Acc: 0.5165
val Loss: 0.9267 Acc: 0.5819

Training complete in 381m 53s
Best val Acc: 0.590517
Best val epoch: 20
```

- (a) For training set: I cropped a random portion of image and resize it to a given size (224x224), and then horizontally flipped the given image randomly with a given probability (p = 0.5). Finally, I normalized a tensor image with mean ([0.485, 0.456, 0.406] for each RGB channel) and standard deviation ([0.229, 0.224, 0.225] for each RGB channel). For validation and testing set: I resized the input image to the given size (256x256), and then cropped the given image at the center with size (224x224). Finally, I normalized a tensor image with mean ([0.485, 0.456, 0.406] for each RGB channel) and standard deviation ([0.229, 0.224, 0.225] for each RGB channel).
- (b) Loss function would be cross-entropy loss; optimizer would be Adam optimizer.
- (c) For the model with training a Resnet18 model from scratch, the number of epochs is 50 (because I reset all of the weights), and the number of epochs is 25 for the other 2 models. For all models, the batch size is 4 and the learning rate is 0.001
- the learning rate is decay by a factor of 0.1 every 7 epochs

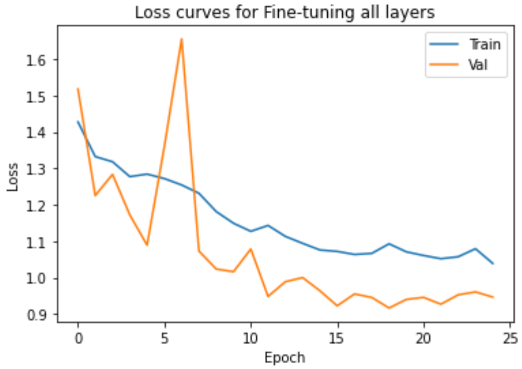
1.2 (a) Generate a plot of training and validation loss curves for each of the three training cases from Section 1.1.1.

In [17]:
```
# plot the loss curve for Fine-tuning only the fully-connected layer
plt.plot(train_losses_FineTuneFC, label='Train')
plt.plot(val_losses_FineTuneFC, label='Val')
plt.legend()
plt.title('Loss curves for Fine-tuning only the fully-connected layer')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.show()
```



- Best epoch: 23; because the model has the highest accuracy in the validation set when epoch = 23

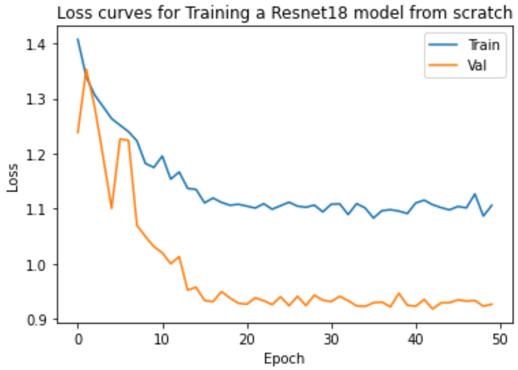
In [15]:
```
# plot the loss curve for Fine-tuning all layers
plt.plot(train_losses_FineTuning_all, label='Train')
plt.plot(val_losses_FineTuning_all, label='Val')
plt.legend()
plt.title('Loss curves for Fine-tuning all layers')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.show()
```



- Best epoch: 19; because the model has the highest accuracy and the lowest loss in the validation set when epoch = 19

In [14]:
```
# plot the loss curve for Training a Resnet18 model from scratch
plt.plot(train_losses_scratch, label='Train')
plt.plot(val_losses_scratch, label='Val')
plt.legend()
plt.title('Loss curves for Training a Resnet18 model from scratch')
plt.xlabel('Epoch')
```

```
plt.ylabel('Loss')
plt.show()
```



- Best epoch: 21; because the model has the highest accuracy in validation set when epoch = 21

1.2 (b) Choose a single best performing model as your final model, and report the confu- sion matrix, per-class accuracy, and weighted F1 score of this model on the validation set.

- Reference: https://pytorch.org/tutorials/beginner/blitz/cifar10_tutorial.html

In [14]:
```
from sklearn.metrics import confusion_matrix, f1_score

correct_pred = {classname: 0 for classname in class_names}
total_pred = {classname: 0 for classname in class_names}

val_predicted = []
val_true = []
with torch.no_grad():
    for i, (inputs, labels) in enumerate(dataloaders['val']):
        inputs = inputs.to(device)
        labels = labels.to(device)
        output = model_FineTuneFC(inputs)
        _, predictions = torch.max(output, 1)
        for label, prediction in zip(labels, predictions):
            if label == prediction:
                correct_pred[class_names[label]] += 1
            total_pred[class_names[label]] += 1
        for j in range(inputs.size()[0]):
            val_true.append(labels[j].cpu().numpy())
            val_predicted.append(predictions[j].cpu().numpy())

print(" ")
print("="*30)
print(" ")
# Confusion Matrix
cm = confusion_matrix(val_true, val_predicted)
ConF_MaX_plot = pd.DataFrame(cm,
                    index=['True: ALB', 'True: NoF', 'True: OTHER', 'True: YFT'],
                    columns=['Pred: ALB', 'Pred: NoF', 'Pred: OTHER', 'Pred: YFT'])
print('Confusion Matrix: ')
print(ConF_MaX_plot)

print(" ")
print("="*30)
print(" ")
# per-class accuracy
```

```
for classname, correct_count in correct_pred.items():
    accuracy = 100 * float(correct_count) / total_pred[classname]
    print(f'Accuracy for class: {classname:5s} is {accuracy:.1f} %')

print(" ")
print("="*30)
print(" ")
# weighted F1 score
val_weighted_F1 = f1_score(val_true, val_predicted, average='weighted')
print('Weighted F1 Score: ',val_weighted_F1)
```

```
/usr/local/lib/python3.7/dist-packages/torch/utils/data/dataloader.py:490: UserWarning: This DataLoader will create 4 worker processes in total. Our suggested max number
of worker in current system is 2, which is smaller than what this DataLoader is going to create. Please be aware that excessive worker creation might get DataLoader runni
ng slow or even freeze, lower the worker number to avoid potential slowness/freeze if necessary.
  cpuset_checked))

==============================

Confusion Matrix:
             Pred: ALB  Pred: NoF  Pred: OTHER  Pred: YFT
True: ALB           57          4            9         13
True: NoF            8         37            0          1
True: OTHER          3          0           27          0
True: YFT            9          1            7         56

==============================

Accuracy for class: ALB   is 68.7 %
Accuracy for class: NoF   is 80.4 %
Accuracy for class: OTHER is 90.0 %
Accuracy for class: YFT   is 76.7 %

==============================

Weighted F1 Score:  0.7637324318041429
```

1.3 Model Performance Evaluation

- Reference: https://gist.github.com/andrewjong/6b02ff237533b3b2c554701fb53d5c4d

In [15]:
```
class ImageFolderWithPaths(datasets.ImageFolder):
    """Customize ImageFolder to retrieve file name
    """
    # override the __getitem__ method.
    def __getitem__(self, index):
        # this is what ImageFolder normally returns
        original_tuple = super(ImageFolderWithPaths, self).__getitem__(index)
        # the image file path
        path = self.imgs[index][0]
        # make a new tuple that includes original and the path
        tuple_with_path = (original_tuple + (path,))
        return tuple_with_path
```

In [16]:
```
test_data_dir = '/content/drive/MyDrive/test colab/Fish/test2'
image_datasets_test = ImageFolderWithPaths(root = test_data_dir, transform = data_transforms['test'])
testloader = torch.utils.data.DataLoader(image_datasets_test, batch_size=4, shuffle=False, num_workers=4)
```

```
/usr/local/lib/python3.7/dist-packages/torch/utils/data/dataloader.py:490: UserWarning: This DataLoader will create 4 worker processes in total. Our suggested max number
of worker in current system is 2, which is smaller than what this DataLoader is going to create. Please be aware that excessive worker creation might get DataLoader runni
ng slow or even freeze, lower the worker number to avoid potential slowness/freeze if necessary.
  cpuset_checked))
```

- Reference: https://pytorch.org/tutorials/beginner/blitz/cifar10_tutorial.html

In [46]:
```
# Predict
test_fileName = []
```

```
test_predicted = []
with torch.no_grad():
    for data in testloader:
        inputs, labels, paths = data
        inputs = inputs.to(device)
        labels = labels.to(device)
        paths2 = list(paths)
        for i in range(len(paths2)):
          paths2[i] = paths2[i].split("/")[-1]
        output = model_FineTuneFC(inputs)
        _, predictions = torch.max(output, 1)
        for j in range(inputs.size()[0]):
            test_predicted.append(predictions.numpy()[j])
            test_fileName.append(paths2[j])
```

```
/usr/local/lib/python3.7/dist-packages/torch/utils/data/dataloader.py:490: UserWarning: This DataLoader will create 4 worker processes in total. Our suggested max number of worker in current system is 2, which is smaller than what this DataLoader is going to create. Please be aware that excessive worker creation might get DataLoader running slow or even freeze, lower the worker number to avoid potential slowness/freeze if necessary.
  cpuset_checked))
```

In [50]:

```
for i in range(len(test_predicted)):
    if test_predicted[i] == 0:
        test_predicted[i] = 'ALB'
    elif test_predicted[i] == 1:
        test_predicted[i] = 'NoF'
    elif test_predicted[i] == 2:
        test_predicted[i] = 'OTHER'
    else:
        test_predicted[i] = 'YFT'
```

In [53]:

```
df = pd.DataFrame(list(zip(test_fileName, test_predicted)))
df
```

Out[53]:

	0	1
0	00nbnyg8lv.jpg	ALB
1	00w6uh7ij9.jpg	YFT
2	03id3d30l2.jpg	ALB
3	05yjz3psm1.jpg	YFT
4	06jxolt55u.jpg	ALB
...	...	...
460	znsx4xkv8w.jpg	YFT
461	zp9z3ikb5l.jpg	ALB
462	zt5hww356w.jpg	YFT
463	zv05q7bkuc.jpg	YFT
464	zzyy3g44t2.jpg	NoF

465 rows × 2 columns

In [55]:

```
# save the predictions
df.to_csv('/content/drive/MyDrive/test colab/F0034WQ_CNN_predictions.csv', index=False, header = False)
```

2

2.1 Data Inspection

In [12]:
```
import re
import spacy
import jovian
from collections import Counter
from torch.utils.data import Dataset, DataLoader
import torch.nn.functional as F
import string
from torch.nn.utils.rnn import pack_padded_sequence, pad_packed_sequence
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import train_test_split
```

In [13]:
```
# Load Data
train = pd.read_csv('/content/drive/MyDrive/test colab/train_yelp_reviews.csv', sep='\t', engine='python')
```

In [14]:
```
train
```

Out[14]:

	text	label
0	Great time - family dinner on a Sunday night.	1
1	The classic Maine Lobster Roll was fantastic.	1
2	We won't be going back.	0
3	All I have to say is the food was amazing!!!	1
4	Food was good, service was good, Prices were g...	1
...	...	...
895	I guess maybe we went on an off night but it w...	0
896	The restaurant atmosphere was exquisite.	1
897	Be sure to order dessert, even if you need to ...	1
898	They could serve it with just the vinaigrette ...	1
899	I had strawberry tea, which was good.	1

900 rows × 2 columns

- Reference: https://jovian.ai/aakanksha-ns/lstm-multiclass-text-classification/v/5?utm_source=embed#C18

In [15]:
```
# calculate sentence lengths
train['text_length'] = train['text'].apply(lambda x: len(x.split()))
train
```

Out[15]:

	text	label	text_length
0	Great time - family dinner on a Sunday night.	1	9
1	The classic Maine Lobster Roll was fantastic.	1	7
2	We won't be going back.	0	5
3	All I have to say is the food was amazing!!!	1	10
4	Food was good, service was good, Prices were g...	1	9
...	...	...	...
895	I guess maybe we went on an off night but it w...	0	13
896	The restaurant atmosphere was exquisite.	1	5
897	Be sure to order dessert, even if you need to ...	1	23
898	They could serve it with just the vinaigrette ...	1	23

	text	label	text_length
899	I had strawberry tea, which was good.	1	7

900 rows × 3 columns

In [25]:
```
#mean sentence length
np.mean(train['text_length'])
```

Out[25]:
```
10.872222222222222
```

- Reference: https://jovian.ai/aakanksha-ns/lstm-multiclass-text-classification/v/5?utm_source=embed#C18

In [16]:
```
#tokenization
import spacy
tok = spacy.load('en_core_web_sm')
def tokenize (text):
    text = re.sub(r"[^\x00-\x7F]+", " ", text)
    regex = re.compile('[' + re.escape(string.punctuation) + '0-9\\r\\t\\n]') # remove punctuation and numbers
    nopunct = regex.sub(" ", text.lower())
    return [token.text for token in tok.tokenizer(nopunct)]
```

- Reference: https://jovian.ai/aakanksha-ns/lstm-multiclass-text-classification/v/5?utm_source=embed#C18

In [23]:
```
#count number of occurences of each word
counts = Counter()
for index, row in train.iterrows():
    counts.update(tokenize(row['text']))
```

Display the most 50 commonly occurring tokens for positive review

In [18]:
```
positive_train = train[train['label'] == 1].copy()
positive_train
```

Out[18]:

	text	label	text_length
0	Great time - family dinner on a Sunday night.	1	9
1	The classic Maine Lobster Roll was fantastic.	1	7
3	All I have to say is the food was amazing!!!	1	10
4	Food was good, service was good, Prices were g...	1	9
5	If you're not familiar, check it out.	1	7
...	...	...	...
893	If you love authentic Mexican food and want a ...	1	25
896	The restaurant atmosphere was exquisite.	1	5
897	Be sure to order dessert, even if you need to ...	1	23
898	They could serve it with just the vinaigrette ...	1	23
899	I had strawberry tea, which was good.	1	7

453 rows × 3 columns

In [19]:
```
counts_positive_train = Counter()
for index, row in positive_train.iterrows():
    counts_positive_train.update(tokenize(row['text']))
```

```
Top50_counts_positive = sorted(counts_positive_train.items(), key=lambda x: x[1], reverse=True)[:50]
print(Top50_counts_positive)
```

```
[('the', 279), (' ', 207), ('and', 202), ('was', 128), ('i', 122), ('a', 98), ('is', 96), ('to', 84), ('good', 66), ('this', 65), ('great', 64), ('it', 57), ('food', 53), ('place', 51), ('in', 50), ('of', 49), ('  ', 45), ('service', 43), ('very', 41), ('for', 38), ('had', 37), ('with', 36), ('you', 35), ('are', 34), ('so', 34), ('were', 32), ('have', 31), ('they', 30), ('we', 29), ('my', 29), ('on', 28), ('here', 27), ('all', 24), ('that', 23), ('friendly', 22), ('delicious', 21), ('amazing', 20), ('back', 20), ('really', 20), ('but', 20), ('best', 20), ('our', 19), ('s', 19), ('nice', 19), ('time', 18), ('t', 18), ('be', 18), ('go', 18), ('just', 17), ('as', 17)]
```

Display the most 50 commonly occurring tokens for negative review

In [20]:
```
negative_train = train[train['label'] == 0].copy()
negative_train
```

Out[20]:

	text	label	text_length
2	We won't be going back.	0	5
6	I probably won't be back, to be honest.	0	8
8	This is a disgrace.	0	4
9	The servers are not pleasant to deal with and ...	0	16
10	The service here leaves a lot to be desired.	0	9
...	...	...	...
887	Don't do it!!!!	0	3
889	Waited and waited and waited.	0	5
891	Waited 2 hours & never got either of our pizza...	0	20
894	I'll take my business dinner dollars elsewhere.	0	7
895	I guess maybe we went on an off night but it w...	0	13

447 rows × 3 columns

In [21]:
```
counts_negative_train = Counter()
for index, row in negative_train.iterrows():
    counts_negative_train.update(tokenize(row['text']))

Top50_counts_negative = sorted(counts_negative_train.items(), key=lambda x: x[1], reverse=True)[:50]
print(Top50_counts_negative)
```

```
[('the', 247), (' ', 198), ('i', 191), ('and', 152), ('was', 138), ('to', 120), ('a', 113), ('not', 92), ('it', 83), ('t', 68), ('of', 68), ('food', 61), ('is', 59), ('for', 57), ('this', 56), ('we', 47), ('in', 47), ('  ', 42), ('that', 42), ('place', 40), ('be', 38), ('my', 37), ('at', 36), ('but', 36), ('back', 33), ('   ', 33), ('service', 32), ('with', 29), ('like', 28), ('very', 28), ('had', 28), ('so', 27), ('were', 27), ('are', 25), ('go', 25), ('there', 25), ('have', 24), ('here', 23), ('they', 22), ('you', 22), ('don', 21), ('good', 20), ('s', 20), ('our', 19), ('on', 19), ('time', 19), ('no', 19), ('will', 18), ('never', 17), ('would', 17)]
```

- good, great, friendly, delicious, best, and nice are words that Naive Bayes or other bag-of-word models may not be able to classify accurately. Because we also need to care about some words near our target words. For example, if there is a 'not' showing in front of 'good', then the meaning would be 'bad'. As a result, the meaning would be totally different, and Naive Bayes or other bag-of-word models are hard to detect or distinguish.

In [22]:
```
# Reference: https://jovian.ai/aakanksha-ns/lstm-multiclass-text-classification/v/5?utm_source=embed#C18
#deleting infrequent words
print("num_words before:",len(counts.keys()))
for word in list(counts):
    if counts[word] < 2:
        del counts[word]
print("num_words after:",len(counts.keys()))
```

```
num_words before: 1919
num_words after: 824
```

In [24]:
```
#creating vocabulary
vocab2index = {"":0, "UNK":1}
```

```
words = ["", "UNK"]
for word in counts:
    vocab2index[word] = len(words)
    words.append(word)
```

In [26]:
```
# Reference: https://jovian.ai/aakanksha-ns/lstm-multiclass-text-classification/v/5?utm_source=embed#C18
def encode_sentence(text, vocab2index, N=20):
    tokenized = tokenize(text)
    encoded = np.zeros(N, dtype=int)
    enc1 = np.array([vocab2index.get(word, vocab2index["UNK"]) for word in tokenized])
    length = min(N, len(enc1))
    encoded[:length] = enc1[:length]
    return encoded, length
```

In [27]:
```
train['encoded'] = train['text'].apply(lambda x: np.array(encode_sentence(x,vocab2index )))
train.head()
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:1: VisibleDeprecationWarning: Creating an ndarray from ragged nested sequences (which is a list-or-tuple of l
ists-or-tuples-or ndarrays with different lengths or shapes) is deprecated. If you meant to do this, you must specify 'dtype=object' when creating the ndarray.
  """Entry point for launching an IPython kernel.
```

Out[27]:

	text	label	text_length	encoded
0	Great time - family dinner on a Sunday night.	1	9	[[2, 3, 4, 5, 6, 7, 8, 9, 10, 0, 0, 0, 0, 0, 0...
1	The classic Maine Lobster Roll was fantastic.	1	7	[[11, 12, 13, 14, 15, 16, 17, 0, 0, 0, 0, 0, 0...
2	We won't be going back.	0	5	[[18, 19, 20, 21, 22, 23, 0, 0, 0, 0, 0, 0, 0,...
3	All I have to say is the food was amazing!!!	1	10	[[24, 25, 26, 27, 28, 29, 11, 30, 16, 31, 4, 0...
4	Food was good, service was good, Prices were g...	1	9	[[30, 16, 32, 33, 34, 16, 32, 33, 35, 36, 32, ...

In [28]:
```
#check how balanced the dataset is
Counter(train['label'])
```

Out[28]: `Counter({0: 447, 1: 453})`

- Pretty balanced

In [29]:
```
# Split data set
X = list(train['encoded'])
y = list(train['label'])
from sklearn.model_selection import train_test_split
X_train, X_valid, y_train, y_valid = train_test_split(X, y, test_size=0.2)
```

2.2 Model Training

- First, I calculated the text length for each review. Next, I removed punctuation, numbers, and special characters, and lowercase the text. Then, en_core_web_sm in spacy package was used for tokenization. After tokenization, I used Counter() to count the number of occurences of each word, and then removed infrequent words (word count < 2).
- Before model training, I created a vocabulary to index mapping and encode our review text. The maximum length of any review is 20 words because the average length of reviews was around 10 (so I decided the maximum length be twice the average length of reviews).
- I split train_yelp_reviews into training and validation set with ratio 8:2. The first layer is the embedding layer, and its input dimension is vocabulary size = 826, and output dimsension of embedding dimension is 100. The second layer is the LSTM layer, its input is the output from the embedding layer, and the dimension of the output of LSTM is 100. For LSTM, I used bidirectional training, and the rate of dropout was 0.3. The final layer is the linear layer, and its input dimension is 100; output dimension is 2. Loss function would be cross-entropy loss; optimizer would be Adam optimizer. The epochs was 125, and learning rate was 0.01

Pytorch Dataset

- Reference: https://jovian.ai/aakanksha-ns/lstm-multiclass-text-classification/v/5?utm_source=embed#C18

In [30]:
```
class ReviewsDataset(Dataset):
    def __init__(self, X, Y):
        self.X = X
        self.y = Y

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

    def __getitem__(self, idx):
        return torch.from_numpy(self.X[idx][0].astype(np.int32)), self.y[idx], self.X[idx][1]
```

In [31]:
```
train_ds = ReviewsDataset(X_train, y_train)
valid_ds = ReviewsDataset(X_valid, y_valid)
```

In [42]:
```
# Reference: https://jovian.ai/aakanksha-ns/lstm-multiclass-text-classification/v/5?utm_source=embed#C18
def train_model(model, epochs=10, lr=0.001):
    parameters = filter(lambda p: p.requires_grad, model.parameters())
    optimizer = torch.optim.Adam(parameters, lr=lr)
    for i in range(epochs):
        model.train()
        sum_loss = 0.0
        total = 0
        for x, y, l in train_dl:
            x = x.long()
            y = y.long()
            y_pred = model(x, l)
            optimizer.zero_grad()
            loss = F.cross_entropy(y_pred, y)
            loss.backward()
            optimizer.step()
            sum_loss += loss.item()*y.shape[0]
            total += y.shape[0]
        val_loss, val_acc, val_rmse = validation_metrics(model, val_dl)
        if i % 5 == 1:
            print("train loss %.3f, val loss %.3f, val accuracy %.3f, and val rmse %.3f" % (sum_loss/total, val_loss, val_acc, val_rmse))

def validation_metrics (model, valid_dl):
    model.eval()
    correct = 0
    total = 0
    sum_loss = 0.0
    sum_rmse = 0.0
    for x, y, l in valid_dl:
        x = x.long()
        y = y.long()
        y_hat = model(x, l)
        loss = F.cross_entropy(y_hat, y)
        pred = torch.max(y_hat, 1)[1]
        correct += (pred == y).float().sum()
        total += y.shape[0]
        sum_loss += loss.item()*y.shape[0]
        sum_rmse += np.sqrt(mean_squared_error(pred, y.unsqueeze(-1)))*y.shape[0]
    return sum_loss/total, correct/total, sum_rmse/total
```

In [34]:
```
batch_size = 64
vocab_size = len(words)
train_dl = DataLoader(train_ds, batch_size=batch_size, shuffle=True)
val_dl = DataLoader(valid_ds, batch_size=batch_size)
```

LSTM model setting

In [72]:
```
# Reference: https://jovian.ai/aakanksha-ns/lstm-multiclass-text-classification/v/5?utm_source=embed#C18
# Reference: https://github.com/bentrevett/pytorch-sentiment-analysis/blob/master/2%20-%20Upgraded%20Sentiment%20Analysis.ipynb
class LSTM_fixed_len(torch.nn.Module) :
    def __init__(self, vocab_size, embedding_dim, hidden_dim, dropout, bidirectional, n_layers) :
```

```
        super().__init__()
        self.embeddings = nn.Embedding(vocab_size, embedding_dim, padding_idx=0)
        self.lstm = nn.LSTM(embedding_dim,
                            hidden_dim,
                            num_layers=n_layers,
                            batch_first=True,
                            bidirectional=bidirectional,
                            dropout=dropout)
        self.linear = nn.Linear(hidden_dim, 2)
        self.dropout = nn.Dropout(dropout)

    def forward(self, x, l):
        x = self.embeddings(x)
        x = self.dropout(x)
        lstm_out, (ht, ct) = self.lstm(x)
        return self.linear(ht[-1])
```

In [75]:

```
model_fixed =  LSTM_fixed_len(vocab_size, 100, 100, dropout = 0.3, bidirectional = True, n_layers = 2)
```

In [76]:

```
train_model(model_fixed, epochs=125, lr=0.01)
```

```
train loss 0.489, val loss 0.608, val accuracy 0.661, and val rmse 0.579
train loss 0.095, val loss 1.267, val accuracy 0.706, and val rmse 0.541
train loss 0.021, val loss 1.449, val accuracy 0.739, and val rmse 0.510
train loss 0.017, val loss 0.912, val accuracy 0.772, and val rmse 0.476
train loss 0.008, val loss 1.316, val accuracy 0.778, and val rmse 0.466
train loss 0.009, val loss 1.289, val accuracy 0.750, and val rmse 0.499
train loss 0.009, val loss 1.235, val accuracy 0.800, and val rmse 0.445
train loss 0.015, val loss 1.199, val accuracy 0.761, and val rmse 0.488
train loss 0.002, val loss 1.312, val accuracy 0.761, and val rmse 0.489
train loss 0.003, val loss 1.456, val accuracy 0.767, and val rmse 0.482
train loss 0.008, val loss 1.573, val accuracy 0.783, and val rmse 0.463
train loss 0.002, val loss 1.462, val accuracy 0.733, and val rmse 0.515
train loss 0.002, val loss 1.633, val accuracy 0.772, and val rmse 0.473
train loss 0.001, val loss 1.744, val accuracy 0.722, and val rmse 0.526
train loss 0.005, val loss 1.445, val accuracy 0.778, and val rmse 0.469
train loss 0.014, val loss 1.460, val accuracy 0.778, and val rmse 0.467
train loss 0.008, val loss 1.197, val accuracy 0.772, and val rmse 0.475
train loss 0.001, val loss 1.300, val accuracy 0.767, and val rmse 0.482
train loss 0.000, val loss 1.443, val accuracy 0.778, and val rmse 0.470
train loss 0.004, val loss 1.604, val accuracy 0.756, and val rmse 0.493
train loss 0.000, val loss 1.653, val accuracy 0.767, and val rmse 0.481
train loss 0.006, val loss 1.519, val accuracy 0.767, and val rmse 0.479
train loss 0.001, val loss 1.599, val accuracy 0.767, and val rmse 0.483
train loss 0.001, val loss 1.315, val accuracy 0.772, and val rmse 0.476
train loss 0.002, val loss 1.539, val accuracy 0.767, and val rmse 0.479
```

2.3 Evaluation

Load testing set

In [82]:

```
test = pd.read_csv('/content/drive/MyDrive/test colab/test_yelp_reviews.csv', sep='\t', engine='python')
test
```

Out[82]:

	text
0	Would not recommend to others.
1	I will be back many times soon.
2	Their steaks are 100% recommended!
3	At first glance it is a lovely bakery cafe - n...
4	We waited an hour for what was a breakfast I c...
...	...
95	The menu is always changing, food quality is g...

	text
96	How can you call yourself a steakhouse if you ...
97	The food sucked, which we expected but it suck...
98	It was a pale color instead of nice and char a...
99	There is nothing authentic about this place.

100 rows × 1 columns

Transform testing set

In [83]:
```
test['encoded'] = test['text'].apply(lambda x: np.array(encode_sentence(x,vocab2index )))
test['text_length'] = test['text'].apply(lambda x: len(x.split()))
test
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:1: VisibleDeprecationWarning: Creating an ndarray from ragged nested sequences (which is a list-or-tuple of l
ists-or-tuples-or ndarrays with different lengths or shapes) is deprecated. If you meant to do this, you must specify 'dtype=object' when creating the ndarray.
  """Entry point for launching an IPython kernel.
```

Out[83]:

	text	encoded	text_length
0	Would not recommend to others.	[[289, 40, 290, 27, 691, 0, 0, 0, 0, 0, 0, 0, ...	5
1	I will be back many times soon.	[[25, 148, 21, 23, 431, 73, 725, 0, 0, 0, 0, 0...	7
2	Their steaks are 100% recommended!	[[243, 1020, 50, 576, 1, 0, 0, 0, 0, 0, 0, 0, ...	5
3	At first glance it is a lovely bakery cafe - n...	[[112, 123, 1, 43, 29, 8, 814, 1201, 1808, 4, ...	15
4	We waited an hour for what was a breakfast I c...	[[18, 1482, 77, 1166, 88, 144, 16, 8, 253, 25,...	18
...	...	...	...
95	The menu is always changing, food quality is g...	[[11, 234, 29, 61, 1, 33, 30, 167, 29, 22, 760...	15
96	How can you call yourself a steakhouse if you ...	[[81, 284, 38, 1, 1724, 8, 1, 37, 38, 284, 20,...	17
97	The food sucked, which we expected but it suck...	[[11, 30, 1347, 33, 135, 18, 1612, 228, 43, 13...	15
98	It was a pale color instead of nice and char a...	[[43, 16, 8, 1, 1887, 1, 214, 266, 48, 1, 48, ...	14
99	There is nothing authentic about this place.	[[161, 29, 670, 981, 227, 53, 150, 0, 0, 0, 0,...	7

100 rows × 3 columns

Prediction

In [96]:
```
X = list(test['encoded'])
y = list(test['text_length'])
test2 = ReviewsDataset(X, y)
test3 = DataLoader(test2, batch_size=100)
for x, y, l in test3:
    x = x.long()
    y = y.long()
    pred = model_fixed(x, l)

predictions = torch.max(pred, 1)[1]
predictions
```

Out[96]:
```
tensor([0, 1, 1, 1, 0, 1, 0, 1, 1, 1, 0, 1, 0, 1, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0,
        1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 1, 0, 1, 1, 1, 0, 1, 1, 0, 0,
        1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0,
        1, 0, 1, 0, 1, 0, 1, 0, 0, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 0, 0,
        0, 0, 0, 0])
```

Save

In [98]:
```
Final_pred = predictions.numpy()

df_pred = pd.DataFrame(Final_pred, columns =['classification'])
df_pred
```

Out[98]:

	classification
0	0
1	1
2	1
3	1
4	0
...	...
95	0
96	0
97	0
98	0
99	0

100 rows × 1 columns

In [99]:
```
df_pred.to_csv('/content/drive/MyDrive/test colab/F0034WQ_LSTM_predictions.csv', index=False)
```