```
import numpy as np
import os
import torch
import torchvision
import matplotlib
import matplotlib.pyplot as plt
import tarfile
```

```
matplotlib.rcParams['figure.facecolor']='white'
%matplotlib inline
```

```
url="https://s3.amazonaws.com/fast-ai-imageclas/cifar10.tgz"
torchvision.datasets.utils.download_url(url,".")
```

```
Downloading https://s3.amazonaws.com/fast-ai-imageclas/cifar10.tgz to ./cifar10.tgz
135110656/? [00:03<00:00, 38255644.18it/s]
```

```
with tarfile.open("/content/cifar10.tgz","r:gz") as tar:
    tar.extractall("./data")
```

```
data_dir="/content/data/cifar10"
print(os.listdir(data_dir))
```

```
['train', 'test']
```

```
print(os.listdir(data_dir+"/train"))
```

```
['truck', 'airplane', 'cat', 'deer', 'horse', 'automobile', 'dog', 'frog', 'ship', 'bird']
```

```
stats=((0.4914,0.4822,0.4465),(0.2023,0.1994,0.2010))
train_transform=torchvision.transforms.Compose([
    torchvision.transforms.RandomCrop(32,padding=4,padding_mode='reflect'),
    torchvision.transforms.RandomHorizontalFlip(),
    torchvision.transforms.ToTensor(),
    torchvision.transforms.Normalize(*stats,inplace=True)
])
test_transform=torchvision.transforms.Compose([
    torchvision.transforms.ToTensor(),
    torchvision.transforms.Normalize(*stats)
])
```

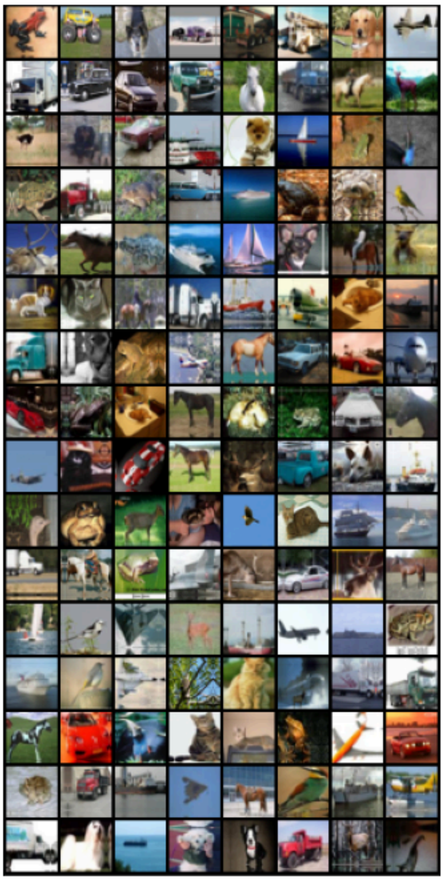
```
train_ds=torchvision.datasets.ImageFolder(data_dir+"/train",transform=train_transform)
test_ds=torchvision.datasets.ImageFolder(data_dir+"/test",transform=test_transform)
```

```
batch_size=128
train_dataloader=torch.utils.data.DataLoader(train_ds,batch_size,shuffle=True,pin_memory=True,num_workers=3)
test_dataloader=torch.utils.data.DataLoader(test_ds,batch_size,pin_memory=True,num_workers=3)
```

```
def denormalize(images,means,stds):
    means=torch.tensor(means).reshape(1,3,1,1)
    stds=torch.tensor(stds).reshape(1,3,1,1)
    return images*stds+means
```

```
def show_batch(dl):
    for images,_ in dl:
        fig,ax=plt.subplots(figsize=(12,12))
        ax.set_xticks([])
        ax.set_yticks([])
        denorm_images=denormalize(images,*stats)
        X=torchvision.utils.make_grid(denorm_images,nrow=8)
        ax.imshow(X.permute(1,2,0).clamp(0,1))
        break
```

```
show_batch(train_dataloader)
```



```python
def get_default_device():
    if torch.cuda.is_available():
        return torch.device("cuda")
    return torch.device("cpu")
```

```python
device=get_default_device()
```

```python
print(device)
```

cuda

```python
def to_device(data,device):
    if isinstance(data,(list,tuple)):
        return [to_device(x,device) for x in data]
    return data.to(device,non_blocking=True)
```

```python
class DataLoader:
    def __init__(self,data,device):
        self.data=data
        self.device=device
    def __len__(self):
        return len(self.data)
    def __iter__(self):
        for x in self.data:
            yield to_device(x,self.device)
```

```python
train_loader=DataLoader(train_dataloader,device)
test_loader=DataLoader(test_dataloader,device)
```

```python
class SimpleResidualNetwork(torch.nn.Module):
    def __init__(self):
        super().__init__()
        self.network=torch.nn.Sequential(
            torch.nn.Conv2d(3,3,kernel_size=3,padding=1,stride=1),
            torch.nn.ReLU(),
            torch.nn.Conv2d(3,3,kernel_size=3,padding=1,stride=1),
            torch.nn.ReLU(),
            torch.nn.Conv2d(3,3,kernel_size=3,padding=1,stride=1),
```

```
            torch.nn.ReLU(),
            torch.nn.Conv2d(3,3,kernel_size=3,padding=1,stride=1),
            torch.nn.ReLU()
        )
    def forward(self,X):
        out=self.network(X)
        return out+X
```

```
model=to_device(SimpleResidualNetwork(),device)
for images,_ in train_loader:
    out=model(images)
    print(out.shape)
    break
torch.cuda.empty_cache()
```

```
torch.Size([128, 3, 32, 32])
```

```
del model,images,out
```

```
def accuracy(pred,labels):
    _,labelp=torch.max(pred,dim=1)
    return torch.tensor(torch.sum(labelp==labels).item()/len(labels))
```

```
class ImageClassificationBase(torch.nn.Module):
    def training_step(self,batch):
        images,labels=batch
        out=self(images)
        loss=torch.nn.functional.cross_entropy(out,labels)
        return loss
    def validation_step(self,batch):
        images,labels=batch
        out=self(images)
        loss=torch.nn.functional.cross_entropy(out,labels)
        acc=accuracy(out,labels)
        return {"val_acc":acc,"val_loss":loss.detach()}
    def validation_epoch_step(self,result):
        loss_=[X["val_loss"] for X in result]
        loss_=torch.stack(loss_).mean()
        acc_=[X["val_acc"] for X in result]
        acc_=torch.stack(acc_).mean()
        return {"val_acc":acc_.item(),"val_loss":loss_.item()}
    def epoch_end(self,epoch,result):
        print("Epoch [{}], last_lr: {:.5f}, train_loss: {:.4f}, val_loss: {:.4f}, val_acc: {:.4f}".format(ep
                result["train_loss"],result["val_loss"],result["val_acc"]))
```

```
def conv_block(in_channels,out_channels,pool=False):
    layers=[torch.nn.Conv2d(in_channels,out_channels,3,padding=1,stride=1),
            torch.nn.BatchNorm2d(out_channels),
            torch.nn.ReLU(inplace=True)]
    if pool:
        layers.append(torch.nn.MaxPool2d(2))
    return torch.nn.Sequential(*layers)
```

```
class Resnet9(ImageClassificationBase):
    def __init__(self,in_channels,num_classes):
        super().__init__()
        self.conv1=conv_block(in_channels,64) # (64,32,32)
        self.conv2=conv_block(64,128,pool=True) # (128,16,16)
        self.res1=torch.nn.Sequential(conv_block(128,128),
                                      conv_block(128,128)) # (128,16,16)
        self.conv3=conv_block(128,256,pool=True) # (256,8,8)
        self.conv4=conv_block(256,512,pool=True) # (512,4,4)
        self.res2=torch.nn.Sequential(conv_block(512,512),
                                      conv_block(512,512)) # (512,4,4)
        self.classifier=torch.nn.Sequential(torch.nn.MaxPool2d(4), # (512,1,1)
                                      torch.nn.Flatten(), # (512)
                                      torch.nn.Dropout(0.1),
                                      torch.nn.Linear(512,num_classes)) # (512,10)
    def forward(self,X):
        out=self.conv1(X)
        out=self.conv2(out)
        out=self.res1(out)+out
```

```
        out=self.conv3(out)
        out=self.conv4(out)
        out=self.res2(out)+out
        out=self.classifier(out)
        return out
```

```
model=to_device(Resnet9(3,10),device)
model
```

```
Resnet9(
  (conv1): Sequential(
    (0): Conv2d(3, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (2): ReLU(inplace=True)
  )
  (conv2): Sequential(
    (0): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (2): ReLU(inplace=True)
    (3): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  )
  (res1): Sequential(
    (0): Sequential(
      (0): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
      (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (2): ReLU(inplace=True)
    )
    (1): Sequential(
      (0): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
      (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (2): ReLU(inplace=True)
    )
  )
  (conv3): Sequential(
    (0): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (2): ReLU(inplace=True)
    (3): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  )
  (conv4): Sequential(
    (0): Conv2d(256, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (2): ReLU(inplace=True)
    (3): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  )
  (res2): Sequential(
    (0): Sequential(
      (0): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
      (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (2): ReLU(inplace=True)
    )
    (1): Sequential(
      (0): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
      (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (2): ReLU(inplace=True)
    )
  )
  (classifier): Sequential(
    (0): MaxPool2d(kernel_size=4, stride=4, padding=0, dilation=1, ceil_mode=False)
    (1): Flatten(start_dim=1, end_dim=-1)
    (2): Dropout(p=0.1, inplace=False)
    (3): Linear(in_features=512, out_features=10, bias=True)
  )
)
```

```
@torch.no_grad()
def evaluate(model,val_dataloader):
    model.eval()
    result=[model.validation_step(batch) for batch in val_dataloader]
    return model.validation_epoch_step(result)


def get_lr(optimizer):
    for param_group in optimizer.param_groups:
        return param_group["lr"]


def fit(epochs,max_lr,model,train_loader,val_loader,weight_decay=0,grad_clip=None,opt_func=torch.optim.SGD):
    torch.cuda.empty_cache()
    history=[]
    optimizer=opt_func(model.parameters(),max_lr,weight_decay=weight_decay)
    sched=torch.optim.lr_scheduler.OneCycleLR(optimizer,max_lr,epochs=epochs,steps_per_epoch=len(train_loade
    for epoch in range(epochs):
        model.train()
```

```
        train_losses=[]
        lrs=[]
        for batch in train_loader:
            loss=model.training_step(batch)
            train_losses.append(loss)
            loss.backward()
            if grad_clip:
                torch.nn.utils.clip_grad_value_(model.parameters(),grad_clip)
            optimizer.step()
            optimizer.zero_grad()
            lrs.append(get_lr(optimizer))
            sched.step()
        result=evaluate(model,val_loader)
        result["train_loss"]=torch.stack(train_losses).mean().item()
        result["lrs"]=lrs
        model.epoch_end(epoch,result)
        history.append(result)
    return history
```

```
history=[evaluate(model,test_loader)]
```

```
print(history)
```

```
[{'val_acc': 0.09068433195352554, 'val_loss': 2.303107976913452}]
```

```
epochs=30
max_lr=0.01
grad_clip=0.1
weight_decay=1e-4
opt_func=torch.optim.Adam
```

```
%%time
history+=fit(epochs,max_lr,model,train_loader,test_loader,weight_decay,grad_clip,opt_func)
```

```
Epoch [0], last_lr: 0.00069, train_loss: 1.2859, val_loss: 1.1011, val_acc: 0.6072
Epoch [1], last_lr: 0.00152, train_loss: 0.8756, val_loss: 1.1396, val_acc: 0.6429
Epoch [2], last_lr: 0.00280, train_loss: 0.7883, val_loss: 0.9213, val_acc: 0.7031
Epoch [3], last_lr: 0.00436, train_loss: 0.7266, val_loss: 1.5677, val_acc: 0.6017
Epoch [4], last_lr: 0.00603, train_loss: 0.6814, val_loss: 0.7590, val_acc: 0.7472
Epoch [5], last_lr: 0.00760, train_loss: 0.6137, val_loss: 0.6092, val_acc: 0.7920
Epoch [6], last_lr: 0.00888, train_loss: 0.5881, val_loss: 0.7308, val_acc: 0.7656
Epoch [7], last_lr: 0.00971, train_loss: 0.5975, val_loss: 0.7278, val_acc: 0.7479
Epoch [8], last_lr: 0.01000, train_loss: 0.5875, val_loss: 0.6630, val_acc: 0.7647
Epoch [9], last_lr: 0.00994, train_loss: 0.5841, val_loss: 0.6608, val_acc: 0.7762
Epoch [10], last_lr: 0.00978, train_loss: 0.5832, val_loss: 0.6613, val_acc: 0.7748
Epoch [11], last_lr: 0.00950, train_loss: 0.5874, val_loss: 0.6310, val_acc: 0.7831
Epoch [12], last_lr: 0.00913, train_loss: 0.5828, val_loss: 0.6087, val_acc: 0.7908
Epoch [13], last_lr: 0.00867, train_loss: 0.5797, val_loss: 0.7576, val_acc: 0.7573
Epoch [14], last_lr: 0.00812, train_loss: 0.5583, val_loss: 0.6877, val_acc: 0.7733
Epoch [15], last_lr: 0.00750, train_loss: 0.5414, val_loss: 0.6047, val_acc: 0.7988
Epoch [16], last_lr: 0.00683, train_loss: 0.5143, val_loss: 0.5726, val_acc: 0.8080
Epoch [17], last_lr: 0.00611, train_loss: 0.4872, val_loss: 0.5471, val_acc: 0.8120
Epoch [18], last_lr: 0.00537, train_loss: 0.4584, val_loss: 0.4396, val_acc: 0.8508
Epoch [19], last_lr: 0.00463, train_loss: 0.4330, val_loss: 0.5637, val_acc: 0.8102
Epoch [20], last_lr: 0.00389, train_loss: 0.4004, val_loss: 0.4005, val_acc: 0.8673
Epoch [21], last_lr: 0.00317, train_loss: 0.3683, val_loss: 0.3924, val_acc: 0.8698
Epoch [22], last_lr: 0.00250, train_loss: 0.3334, val_loss: 0.3344, val_acc: 0.8882
Epoch [23], last_lr: 0.00188, train_loss: 0.2980, val_loss: 0.3323, val_acc: 0.8884
Epoch [24], last_lr: 0.00133, train_loss: 0.2549, val_loss: 0.2989, val_acc: 0.9005
Epoch [25], last_lr: 0.00087, train_loss: 0.2213, val_loss: 0.2951, val_acc: 0.9035
Epoch [26], last_lr: 0.00050, train_loss: 0.1902, val_loss: 0.2766, val_acc: 0.9094
Epoch [27], last_lr: 0.00022, train_loss: 0.1661, val_loss: 0.2636, val_acc: 0.9127
Epoch [28], last_lr: 0.00006, train_loss: 0.1500, val_loss: 0.2589, val_acc: 0.9165
Epoch [29], last_lr: 0.00000, train_loss: 0.1440, val_loss: 0.2574, val_acc: 0.9170
CPU times: user 4min 36s, sys: 33 s, total: 5min 9s
Wall time: 18min
```

```
evaluate(model,test_loader)
```

```
{'val_acc': 0.9170292615890503, 'val_loss': 0.25743985176086426}
```

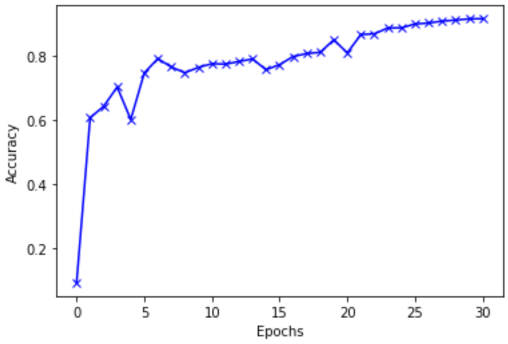
```
print(history[0])
```

```
{'val_acc': 0.09068433195352554, 'val_loss': 2.303107976913452}
```

```
def plot_accuracies(result):
    acc=[X["val_acc"] for X in result]
```

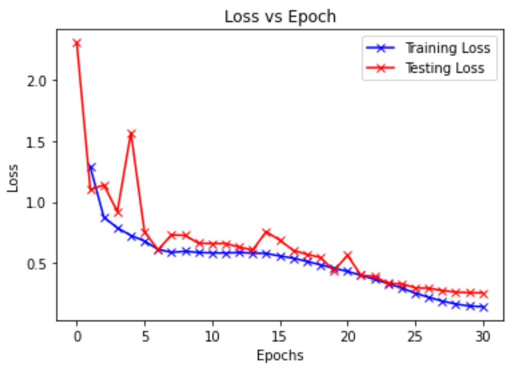
```
    plt.plot(acc,"-bx")
    plt.xlabel("Epochs")
    plt.ylabel("Accuracy")
    plt.show()
```

```
plot_accuracies(history)
```



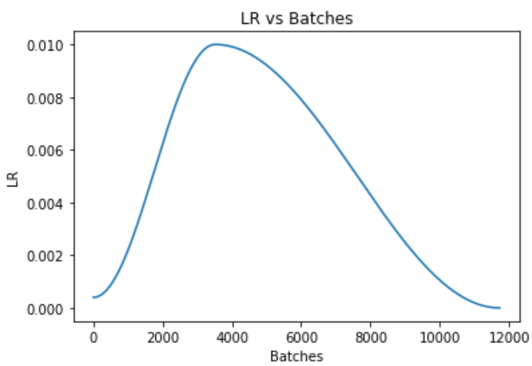

```
def plot_losses(result):
    train_loss=[X.get("train_loss") for X in result]
    test_loss=[X.get("val_loss") for X in result]
    plt.plot(train_loss,"-bx")
    plt.plot(test_loss,"-rx")
    plt.xlabel("Epochs")
    plt.ylabel("Loss")
    plt.title("Loss vs Epoch")
    plt.legend(['Training Loss','Testing Loss'])
    plt.show()
```

```
plot_losses(history)
```




```
def plot_lr(result):
    lrs=np.concatenate([x.get("lrs",[]) for x in result])
    plt.plot(lrs)
    plt.xlabel("Batches")
    plt.ylabel("LR")
    plt.title("LR vs Batches")
    plt.show()
```

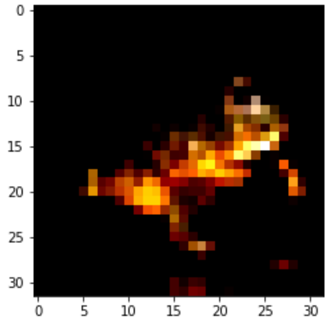
```
plot_lr(history)
```



```
def predict_img(img,model):
    img_=to_device(img.unsqueeze(0),device)
    out=model(img_)
    _,predl=torch.max(out,dim=1)
    return train_ds.classes[predl[0].item()]
```

```
img,label=test_ds[6153]
plt.imshow(img.permute(1,2,0))
y=predict_img(img,model)
print("Label: {}, Predicted Label: {}".format(test_ds.classes[label],y))
```

```
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
Label: frog, Predicted Label: frog
```



```
torch.save(model.state_dict(),"first.pth")
```