# PYTORCH 101

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Credits:
11-785
Soumith Chintala's PyTorch tutorial

# WHAT IS PYTORCH

- PyTorch is a scientific computing package, just like Numpy. What makes it different?
- It’s optimized for leveraging the power of GPUs (Graphics Processing Unit)
- Also, it’s deeply embedded in Python, which makes it extremely easy to use

# THE POWER OF PYTORCH

- GPU support for parallel computation
- Some basic neural layers to combine in your models
- Enforce a general way to code your models
- And most importantly, automatic backpropagation

# TENSORS

- Tensors are very similar to `numpy.ndarrays`, with the extra support of performing operations on those on GPUs
- Thus we have to tell PyTorch where we want to place these tensors and be careful when performing operations
- Let's have a look at Tensors in action!

# AUTOGRAD! - CONVENTIONAL PIPELINE

- Initialize parameters
- Repeat until convergence:
  - Compute Loss
  - Compute gradients of the Loss function w.r.t parameter
  - Update parameters

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The autograd package provides automatic differentiation for all operations on Tensors.

# AUTOGRAD!

- It is a define-by-run framework, which means that your backprop is defined by how your code is run, and that every single iteration can be different.

- `torch.Tensor` is the central class of the package. If you set its attribute `.requires_grad = True`, it starts to track all operations on it. When you finish your computation you can call `.backward()` and have all the gradients computed automatically. The gradient for this tensor will be accumulated into .grad attribute.

- To stop a tensor from tracking history, you can call `.detach()` to detach it from the computation history, and to prevent future computation from being tracked.

- To prevent tracking history (and using memory), you can also wrap the code block in `with torch.no_grad():`

# TORCH.NN

- A Neural Network, as we know is just a composition of operations, to yield highly complex functions.
- `torch.nn` provides a very easy way to implement Neural Networks by stacking different basic layers!
- It relies on `torch.autograd` to calculate the gradients for each of the model parameters, and thus we don't need to worry about implementing the backpropogation
- Let's implement a very simple NN now!

# SAVING AND LOADING MODELS

```
In [24]: print(net.state_dict().keys())
         print(optimizer.state_dict().keys())
         ckpt = {
                 'params': net.state_dict(),
                 'optim': optimizer.state_dict()
                }
         torch.save(ckpt, 'ckpt.pth')

         odict_keys(['conv1.weight', 'conv1.bias', 'conv2.weight', 'conv2.bias', 'fc1.weight', 'fc1.bias', 'fc2.weight', 'fc2.
         bias', 'fc3.weight', 'fc3.bias'])
         dict_keys(['state', 'param_groups'])
```

Saving

```
In [27]: ckpt = torch.load('ckpt.pth')
         net.load_state_dict(ckpt['params'], strict=True)
         optimizer.load_state_dict(ckpt['optim'])
```

Loading

# WORKING WITH DATA LOADERS

```python
import torch
from torch.utils import data

class Dataset(data.Dataset):
  'Characterizes a dataset for PyTorch'
  def __init__(self, list_IDs, labels):
        'Initialization'
        self.labels = labels
        self.list_IDs = list_IDs

  def __len__(self):
        'Denotes the total number of samples'
        return len(self.list_IDs)

  def __getitem__(self, index):
        'Generates one sample of data'
        # Select sample
        ID = self.list_IDs[index]

        # Load data and get label
        X = torch.load('data/' + ID + '.pt')
        y = self.labels[ID]

        return X, y
```

Dataset Class

Dataset Class

# WORKING WITH DATA LOADERS

CLASS torch.utils.data.DataLoader(*dataset*, *batch_size=1*, *shuffle=False*, *sampler=None*, *batch_sampler=None*, *num_workers=0*, *collate_fn=None*, *pin_memory=False*, *drop_last=False*, *timeout=0*, *worker_init_fn=None*, *multiprocessing_context=None*) [SOURCE]

Dataloader

```
for x, y in dataloader:
    output = model(x)
    loss = criterion(output, y)
```

# TORCHVISION TRANSFORMS

```
torchvision.transforms.Normalize(mean, std, inplace=False)
```

```
torchvision.transforms.ToTensor
```

Pre-processing

```
torchvision.transforms.RandomResizedCrop(size, scale=(0.08, 1.0), ratio=(0.75, 1.3333333333333333), interpolation=2)
```

```
torchvision.transforms.RandomRotation(degrees, resample=False, expand=False, center=None, fill=0)
```

```
torchvision.transforms.RandomHorizontalFlip(p=0.5)
```

```
torchvision.transforms.RandomGrayscale(p=0.1)
```

Augmentation

```
>>> transforms.Compose([
>>>     transforms.CenterCrop(10),
>>>     transforms.ToTensor(),
>>> ])
```

Composing them

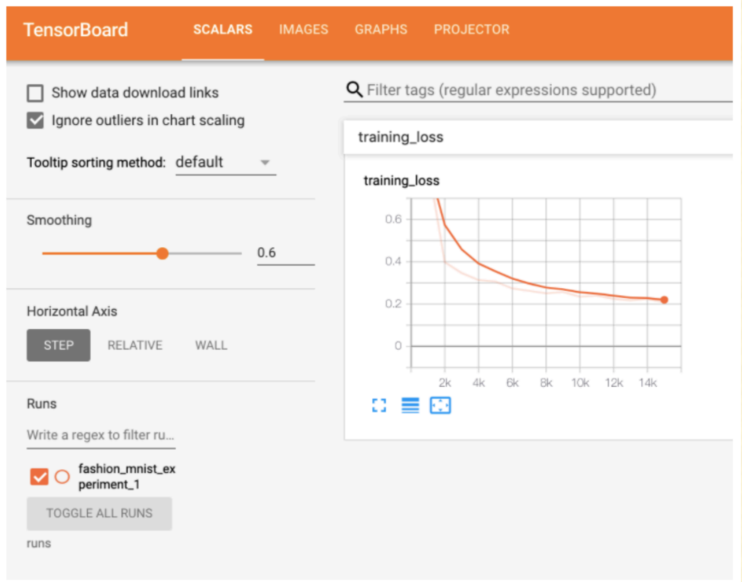
# CRASH COURSE INTO TENSORBOARD

```python
from torch.utils.tensorboard import SummaryWriter

# default `log_dir` is "runs" - we'll be more specific here
writer = SummaryWriter('runs/fashion_mnist_experiment_1')
```

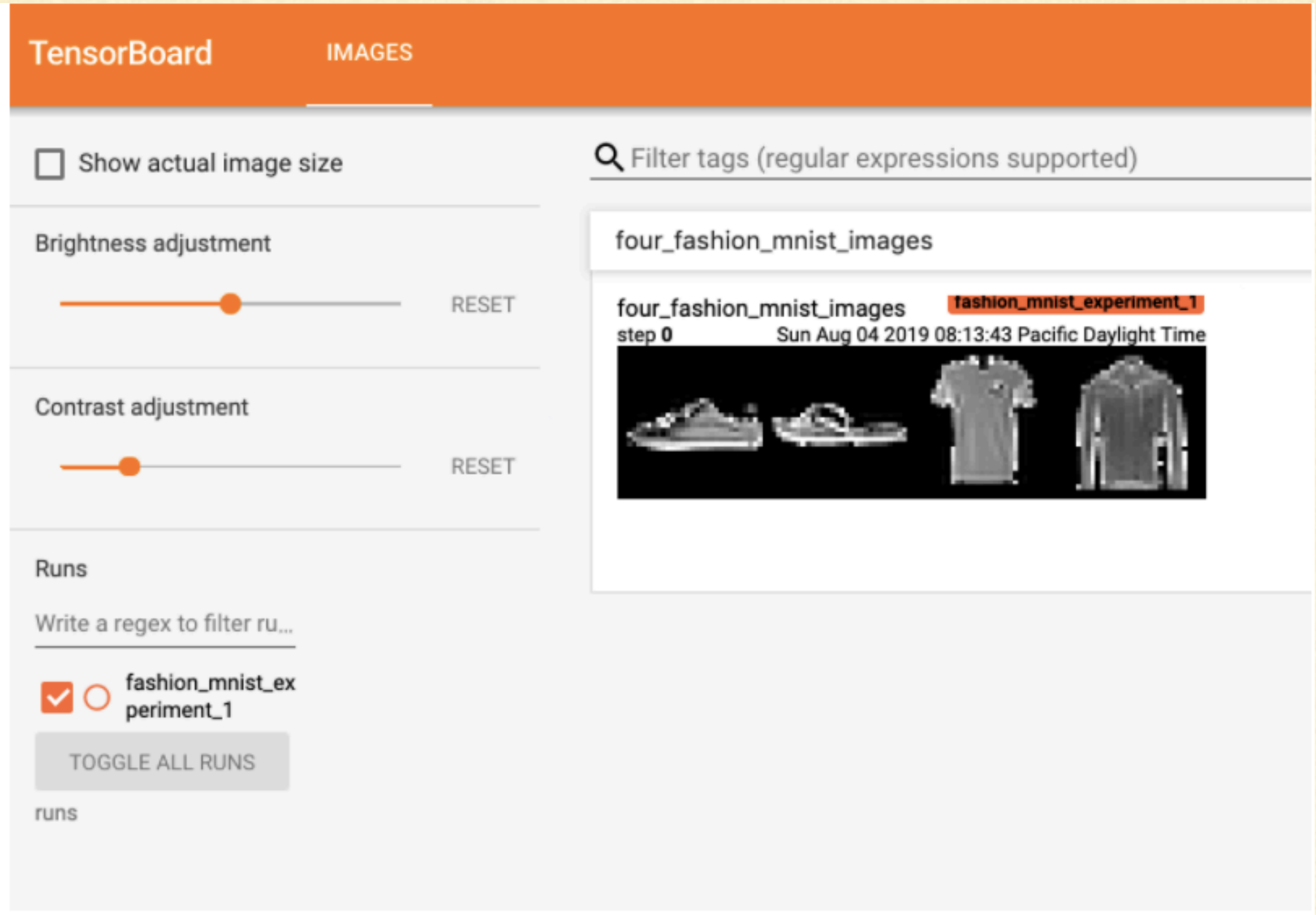
```python
# ...log the running loss
writer.add_scalar('training loss',
                  running_loss / 1000,
                  epoch * len(trainloader) + i)
```

```
tensorboard --logdir=runs
```



# CRASH COURSE INTO TENSORBOARD

```
# write to tensorboard
writer.add_image('four_fashion_mnist_images', img_grid)
```



# SOME COMMON ERRORS!

- Size mismatch. (Try checking tensor.size())
- * is element-wise product.
- Ensure that the tensors are on the same devices!

```
x = 2* torch.ones(2,2)
y = 3* torch.ones(2,2)
print(x * y)
print(x.matmul(y))
```

```
tensor([[ 6.,  6.],
        [ 6.,  6.]])
tensor([[ 12.,  12.],
        [ 12.,  12.]])
```

# SOME COMMON ERRORS!

- .view() v/s .transpose()

```
x = torch.tensor([[1,2,3],[4,5,6]])
print(x)
print(x.t())
print(x.view(3,2))
```

```
tensor([[ 1,  2,  3],
        [ 4,  5,  6]])
tensor([[ 1,  4],
        [ 2,  5],
        [ 3,  6]])
tensor([[ 1,  2],
        [ 3,  4],
        [ 5,  6]])
```

# SOME COMMON ERRORS!

- OOM error!

```
net = nn.Sequential(nn.Linear(2048,2048),nn.ReLU(),
                    nn.Linear(2048,2048),nn.ReLU(),
                    nn.Linear(2048,2048),nn.ReLU(),
                    nn.Linear(2048,2048),nn.ReLU(),
                    nn.Linear(2048,2048),nn.ReLU(),
                    nn.Linear(2048,2048),nn.ReLU(),
                    nn.Linear(2048,120))
x = torch.ones(256,2048)
y = torch.zeros(256).long()
net.cuda()
x.cuda()
crit=nn.CrossEntropyLoss()
out = net(x)
loss = crit(out,y)
loss.backward()
```

# SOME COMMON ERRORS!

- Any guesses?

```
net = nn.Linear(4,2)
x = torch.tensor([1,2,3,4])
y = net(x)
print(y)
```

# SOME COMMON ERRORS!

- Any guesses?

```
net = nn.Linear(4,2)
x = torch.tensor([1,2,3,4])
y = net(x)
print(y)
```

```
net = nn.Linear(4,2)
x = torch.tensor([1,2,3,4])
y = net(x)
print(y)
```

```
RuntimeError: Expected object of type torch.LongTensor but found type torch.FloatTensor
```

```
x = x.float()
x = torch.tensor([1.,2.,3.,4.])
```

# SOME COMMON ERRORS!

- Anything fishy here?

```
class MyNet(nn.Module):
    def __init__(self,n_hidden_layers):
        super(MyNet,self).__init__()
        self.n_hidden_layers=n_hidden_layers
        self.final_layer = nn.Linear(128,10)
        self.act = nn.ReLU()
        self.hidden = []
        for i in range(n_hidden_layers):
            self.hidden.append(nn.Linear(128,128))


    def forward(self,x):
        h = x
        for i in range(self.n_hidden_layers):
            h = self.hidden[i](h)
            h = self.act(h)
        out = self.final_layer(h)
        return out
```

# SOME COMMON ERRORS!

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        self.hidden = []
        for i in range(n_hidden_layers):
            self.hidden.append(nn.Linear(128,128))

    def forward(self,x):
        h = x
        for i in range(self.n_hidden_layers):
            h = self.hidden[i](h)
            h = self.act(h)
        out = self.final_layer(h)
        return out
```

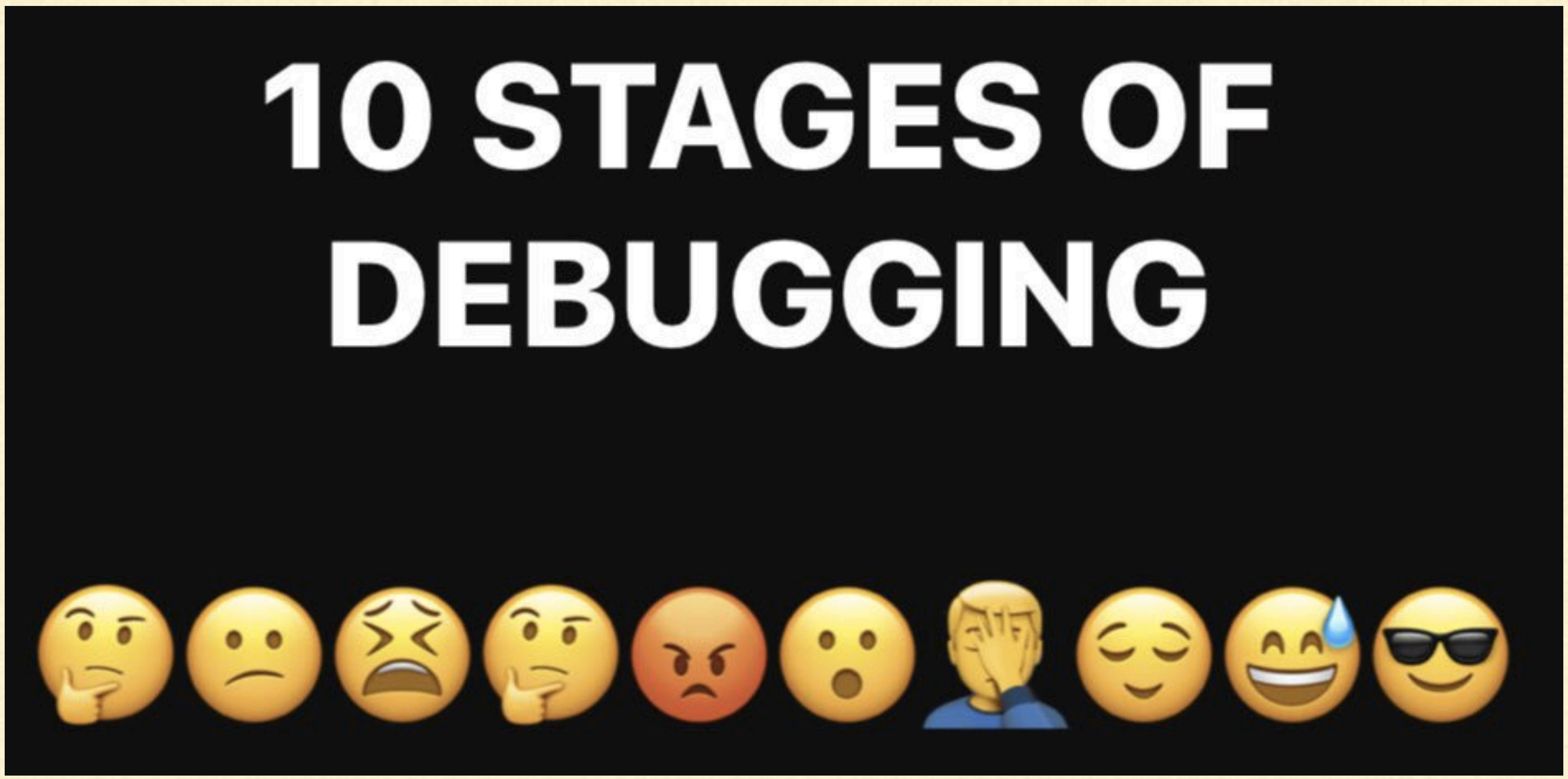
# SOME COMMON ERRORS!

- Identification as a parameter

```
class MyNet(nn.Module):
    def __init__(self,n_hidden_layers):
        super(MyNet,self).__init__()
        self.n_hidden_layers=n_hidden_layers
        self.final_layer = nn.Linear(128,10)
        self.act = nn.ReLU()
        self.hidden = []
        for i in range(n_hidden_layers):
            self.hidden.append(nn.Linear(128,128))
        self.hidden = nn.ModuleList(self.hidden)

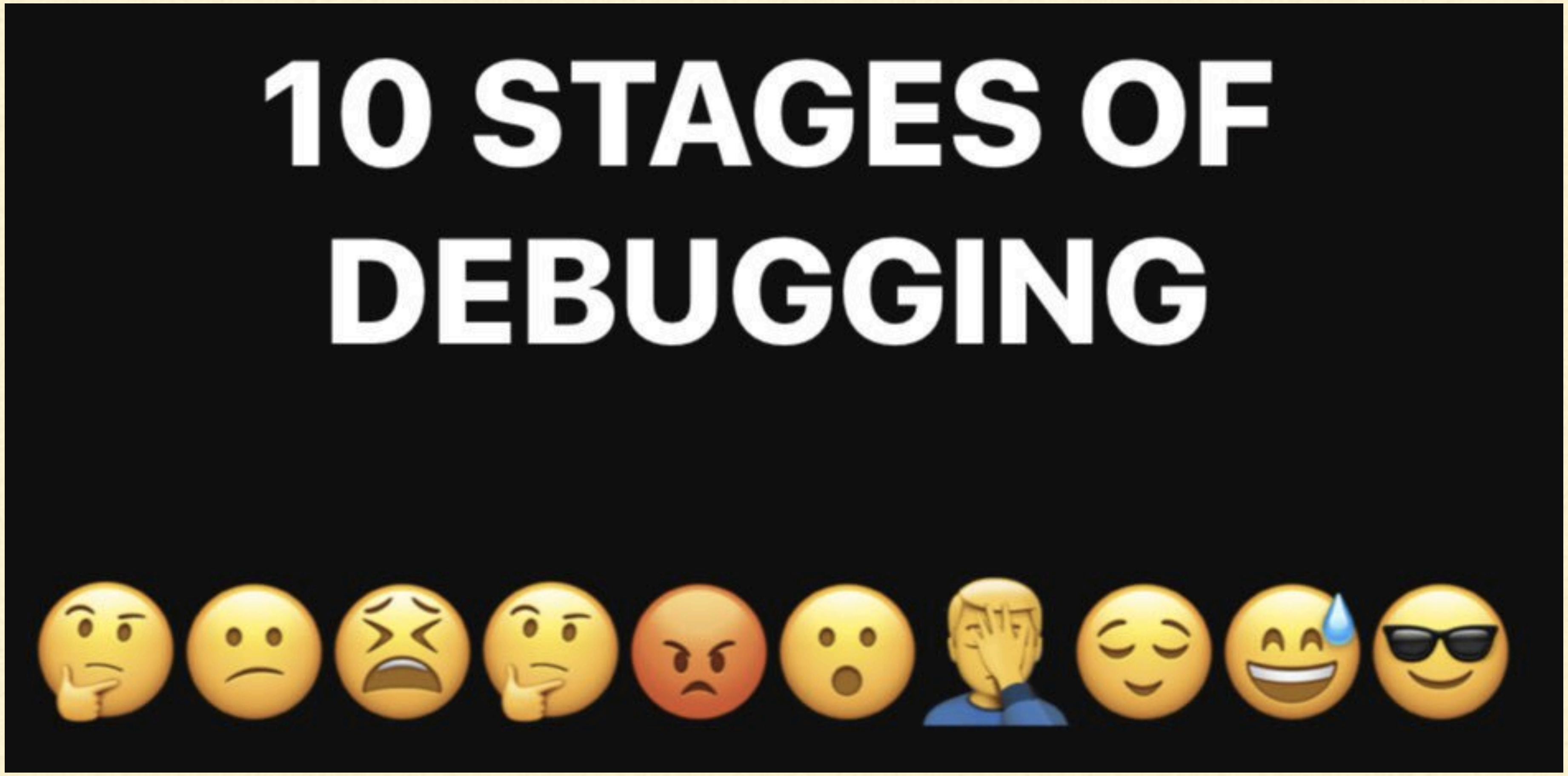
    def forward(self,x):
        h = x
        for i in range(self.n_hidden_layers):
            h = self.hidden[i](h)
            h = self.act(h)
        out = self.final_layer(h)
        return out
```

# DEBUGGING!




Let's post on Piazza!

# DEBUGGING!




You'll learn the most this way!

# DEBUGGING - TIPS!

- **Use a debugger!** `import pdb; pdb.set_trace()`
- **Tons of online resources,** great pytorch documentation, and basically every error is somewhere on stackoverflow.
- **Use Piazza -** First check if someone else has encountered the same bug before making a new post. We will maintain an FAQ
- **Come to Office Hours!**

# THAT'S ALL FOLKS!