The sequential module

DEEP LEARNING WITH PYTORCH

Ismail Elezi
Ph.D. Student of Deep Learning

AlexNet - declaring the modules

```
class AlexNet(nn.Module):

    def __init__(self, num_classes=1000):
        super(AlexNet, self).__init__()
        self.conv1 = nn.Conv2d(3, 64, kernel_size=11, stride=4, padding=2)
        self.relu = nn.ReLU(inplace=True)
        self.maxpool = nn.MaxPool2d(kernel_size=3, stride=2)
        self.conv2 = nn.Conv2d(64, 192, kernel_size=5, padding=2)
        self.conv3 = nn.Conv2d(192, 384, kernel_size=3, padding=1)
        self.conv4 = nn.Conv2d(384, 256, kernel_size=3, padding=1)
        self.conv5 = nn.Conv2d(256, 256, kernel_size=3, padding=1)
        self.avgpool = nn.AdaptiveAvgPool2d((6, 6))
        self.fc1 = nn.Linear(256 * 6 * 6, 4096)
        self.fc2 = nn.Linear(4096, 4096)
        self.fc3 = nn.Linear(4096, num_classes)
```

AlexNet - forward() methods

```
    def forward(self, x):
        x = self.relu(self.conv1(x))
        x = self.maxpool(x)
        x = self.relu(self.conv2(x))
        x = self.maxpool(x)
        x = self.relu(self.conv3(x))
        x = self.relu(self.conv4(x))
        x = self.relu(self.conv5(x))
        x = self.maxpool(x)
        x = self.avgpool(x)
        x = x.view(x.size(0), 256 * 6 * 6)
        x = self.relu(self.fc1(x))
        x = self.relu(self.fc2(x))
        return self.fc3(x)

net = AlexNet()
```

The sequential module - declaring the modules

```
class AlexNet(nn.Module):

    def __init__(self, num_classes=1000):
        super(AlexNet, self).__init__()
        self.features = nn.Sequential(
            nn.Conv2d(3, 64, kernel_size=11, stride=4, padding=2), nn.ReLU(inplace=True),
            nn.MaxPool2d(kernel_size=3, stride=2), nn.Conv2d(64, 192, kernel_size=5, padding=2),
            nn.ReLU(inplace=True), nn.MaxPool2d(kernel_size=3, stride=2),
            nn.Conv2d(192, 384, kernel_size=3, padding=1), nn.ReLU(inplace=True),
            nn.Conv2d(384, 256, kernel_size=3, padding=1), nn.ReLU(inplace=True),
            nn.Conv2d(256, 256, kernel_size=3, padding=1), nn.ReLU(inplace=True),
            nn.MaxPool2d(kernel_size=3, stride=2),)
        self.avgpool = nn.AdaptiveAvgPool2d((6, 6))
        self.classifier = nn.Sequential(
            nn.Dropout(), nn.Linear(256 * 6 * 6, 4096), nn.ReLU(inplace=True),
            nn.Dropout(), nn.Linear(4096, 4096), nn.ReLU(inplace=True), nn.Linear(4096, num_classes)
```

The sequential module - forward() method

```
    def forward(self, x):
        x = self.features(x)
        x = self.avgpool(x)
        x = x.view(x.size(0), 256 * 6 * 6)
        x = self.classifier(x)
        return x
```

Let's practice!

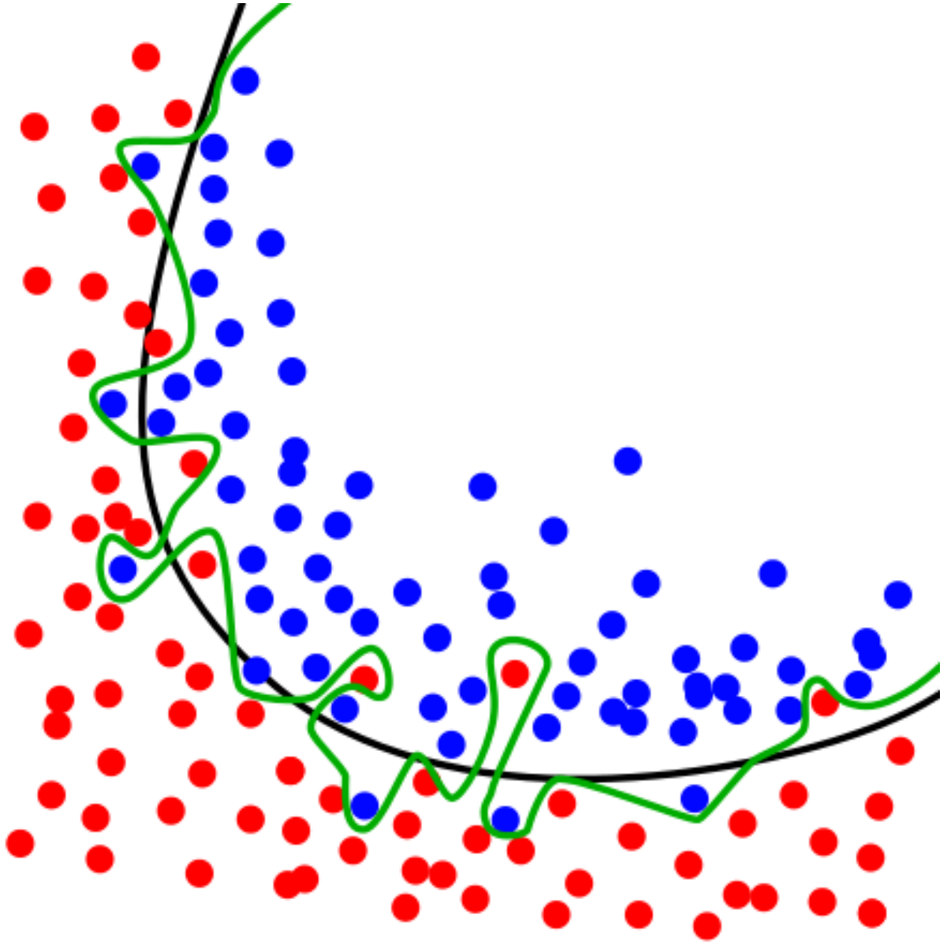
DEEP LEARNING WITH PYTORCH

The problem of overfitting

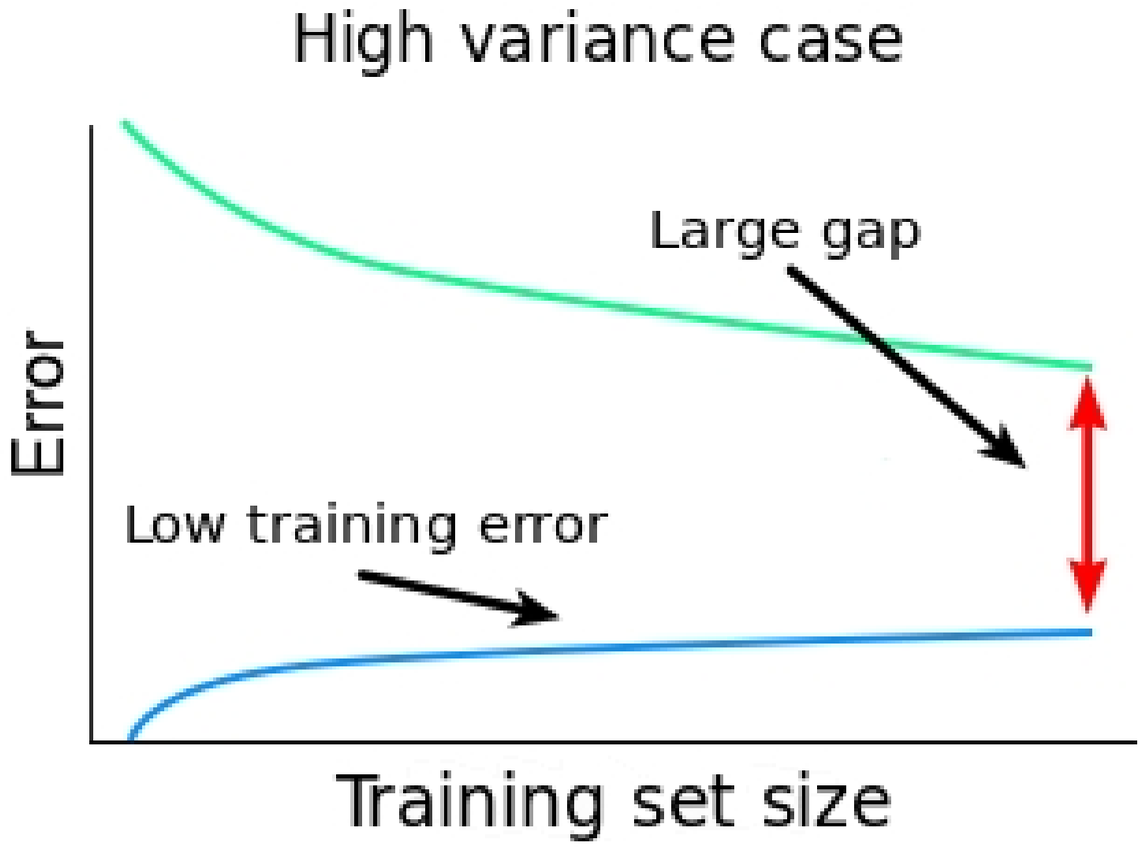
DEEP LEARNING WITH PYTORCH

Ismail Elezi
Ph.D. Student of Deep Learning

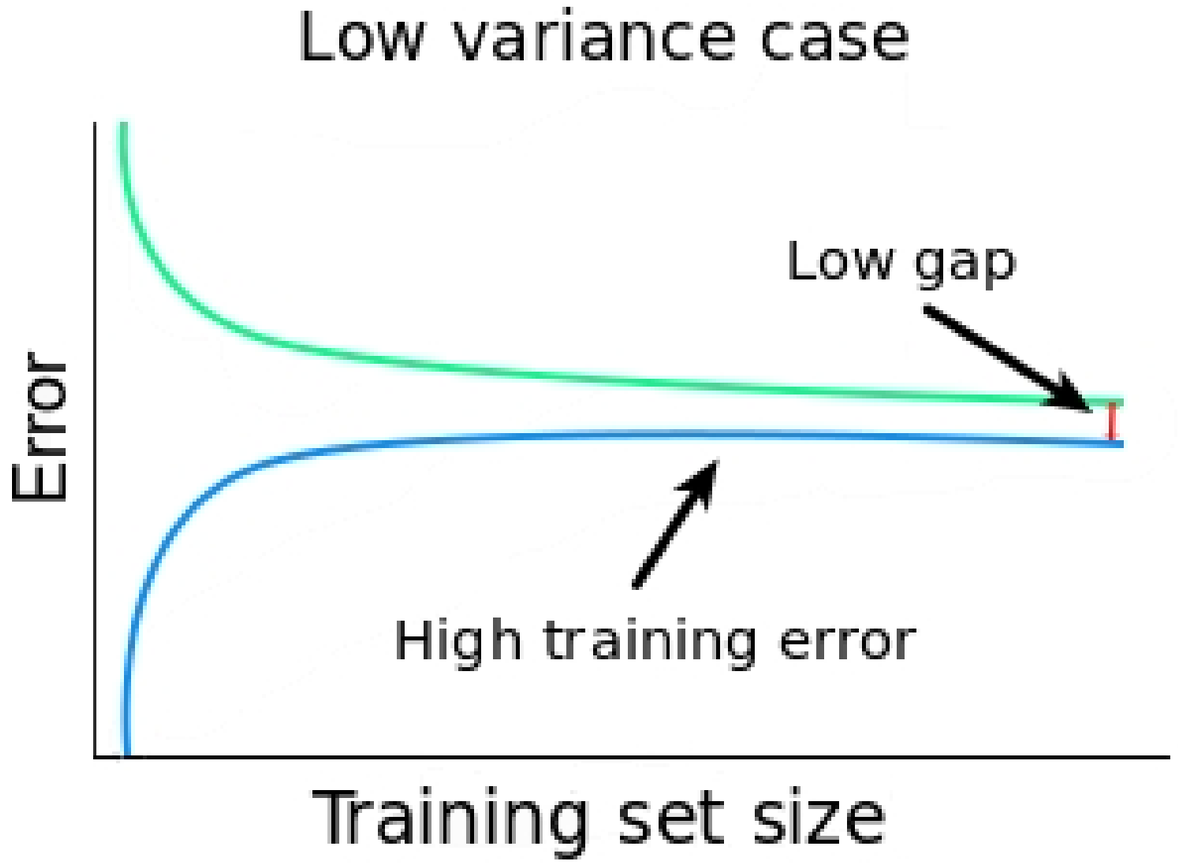
Overfitting



Detecting overfitting



Detecting overfitting



Overfitting in the testing set

- Training set
- Validation set
- Testing set

Validation set

- Training set: train the model
- Validation set: select the model
- Testing set: test the model

Using validation sets in PyTorch

```
indices = np.arange(50000)
np.random.shuffle(indices)

train_loader = torch.utils.data.DataLoader(
    datasets.CIFAR10(root='./data', train=True, download=True,
                     transform=transforms.Compose([transforms.ToTensor(),
                     transforms.Normalize((0.485, 0.456, 0.406), (0.229, 0.224, 0.225))])),
    batch_size=1, shuffle=False, sampler=torch.utils.data.SubsetRandomSampler(indices[:45000]))

val_loader = torch.utils.data.DataLoader(
    datasets.CIFAR10(root='./data', train=True, download=True,
                     transform=transforms.Compose([transforms.ToTensor(),
                     transforms.Normalize((0.485, 0.456, 0.406), (0.229, 0.224, 0.225))])),
    batch_size=1, shuffle=False, sampler=torch.utils.data.SubsetRandomSampler(indices[45000:50000]))
```

Let's practice!

DEEP LEARNING WITH PYTORCH

Regularization techniques

DEEP LEARNING WITH PYTORCH

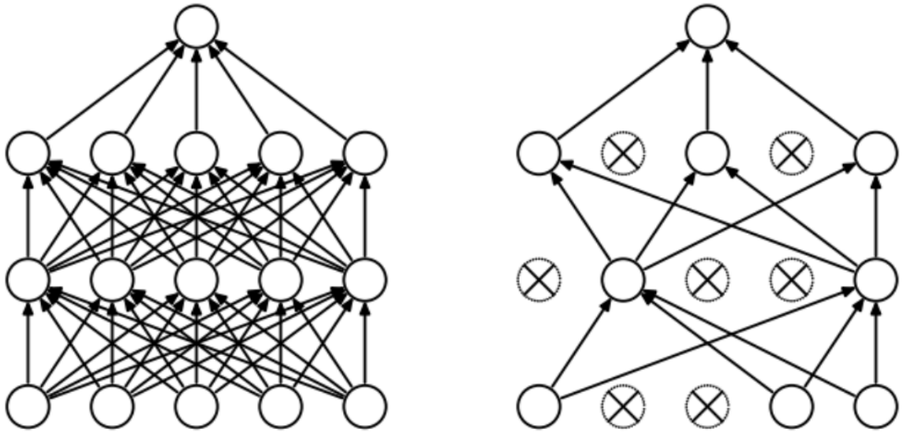
Ismail Elezi
Ph.D. Student of Computer Science

L2-regularization

$$C = -\frac{1}{n}\sum_{xj}\left[y_j \ln a_j^L + (1-y_j)\ln(1-a_j^L)\right] + \frac{\lambda}{2n}\sum_w w^2$$

```
optimizer = optim.Adam(net.parameters(), lr=3e-4, weight_decay=0.0001)
```

Dropout



(a) Standard Neural Net

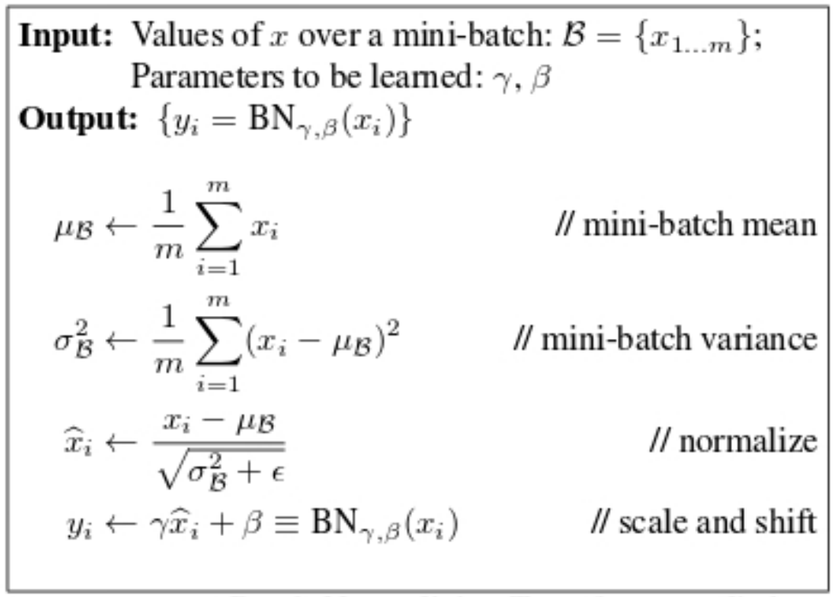
(b) After applying dropout.

[1] Srivastava, Hinton, Krizhevsky, Sutskever, Salakhutdinov; Dropout: a simple way to prevent neural networks from overfitting, JMLR 2014

Dropout in AlexNet - PyTorch code

```
        self.classifier = nn.Sequential(
            nn.Dropout(p=0.5),
            nn.Linear(256 * 6 * 6, 4096),
            nn.ReLU(inplace=True),
            nn.Dropout(p=0.5),
            nn.Linear(4096, 4096),
            nn.ReLU(inplace=True),
            nn.Linear(4096, num_classes),
        )
```

Batch-normalization



Input: Values of x over a mini-batch: $\mathcal{B} = \{x_{1...m}\}$;
Parameters to be learned: γ, β
Output: $\{y_i = \mathrm{BN}_{\gamma,\beta}(x_i)\}$

$$\mu_{\mathcal{B}} \leftarrow \frac{1}{m}\sum_{i=1}^{m} x_i \qquad \text{// mini-batch mean}$$

$$\sigma^2_{\mathcal{B}} \leftarrow \frac{1}{m}\sum_{i=1}^{m}(x_i - \mu_{\mathcal{B}})^2 \qquad \text{// mini-batch variance}$$

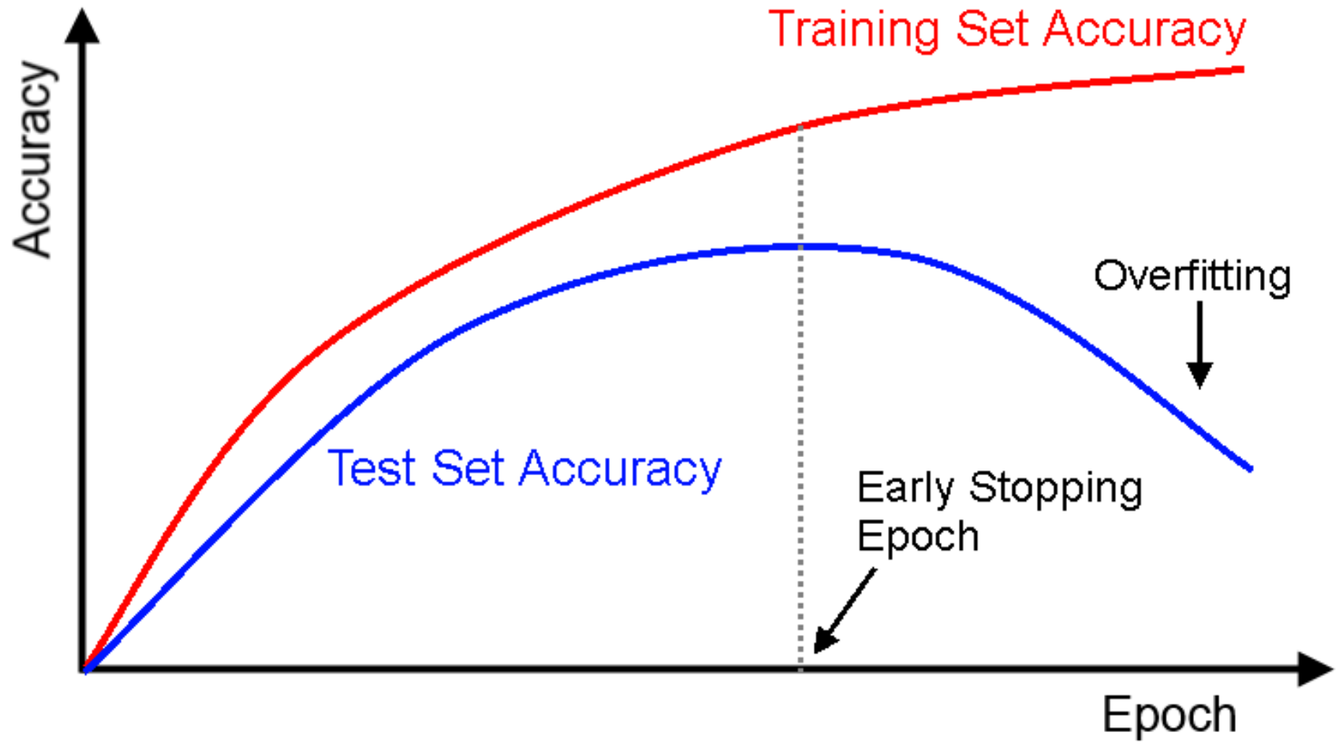
$$\widehat{x}_i \leftarrow \frac{x_i - \mu_{\mathcal{B}}}{\sqrt{\sigma^2_{\mathcal{B}} + \epsilon}} \qquad \text{// normalize}$$

$$y_i \leftarrow \gamma\widehat{x}_i + \beta \equiv \mathrm{BN}_{\gamma,\beta}(x_i) \qquad \text{// scale and shift}$$

```
self.bn = nn.BatchNorm2d(num_features=64, eps=1e-05, momentum=0.9)
```

[1] Ioffe and Szegedy; Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift, ICML 2015

Early-stopping



Hyperparameters

Question: How to choose all these hyperparameters (I2 regularization, dropout parameter, optimizers (Adam vs gradient descent etc), batch-norm momentum and epsilon, number of epochs for early stopping etc)?

Answer: Train many networks with different hyperparameters (typically use random values for them), and test them in the validation set. Then use the best performing net in the validation set to know the expected accuracy of the network in new data.

Eval() mode

```
# Sets the net in train mode
model.train()

# Sets the net in evaluation mode
model.eval()
```

Let's practice!

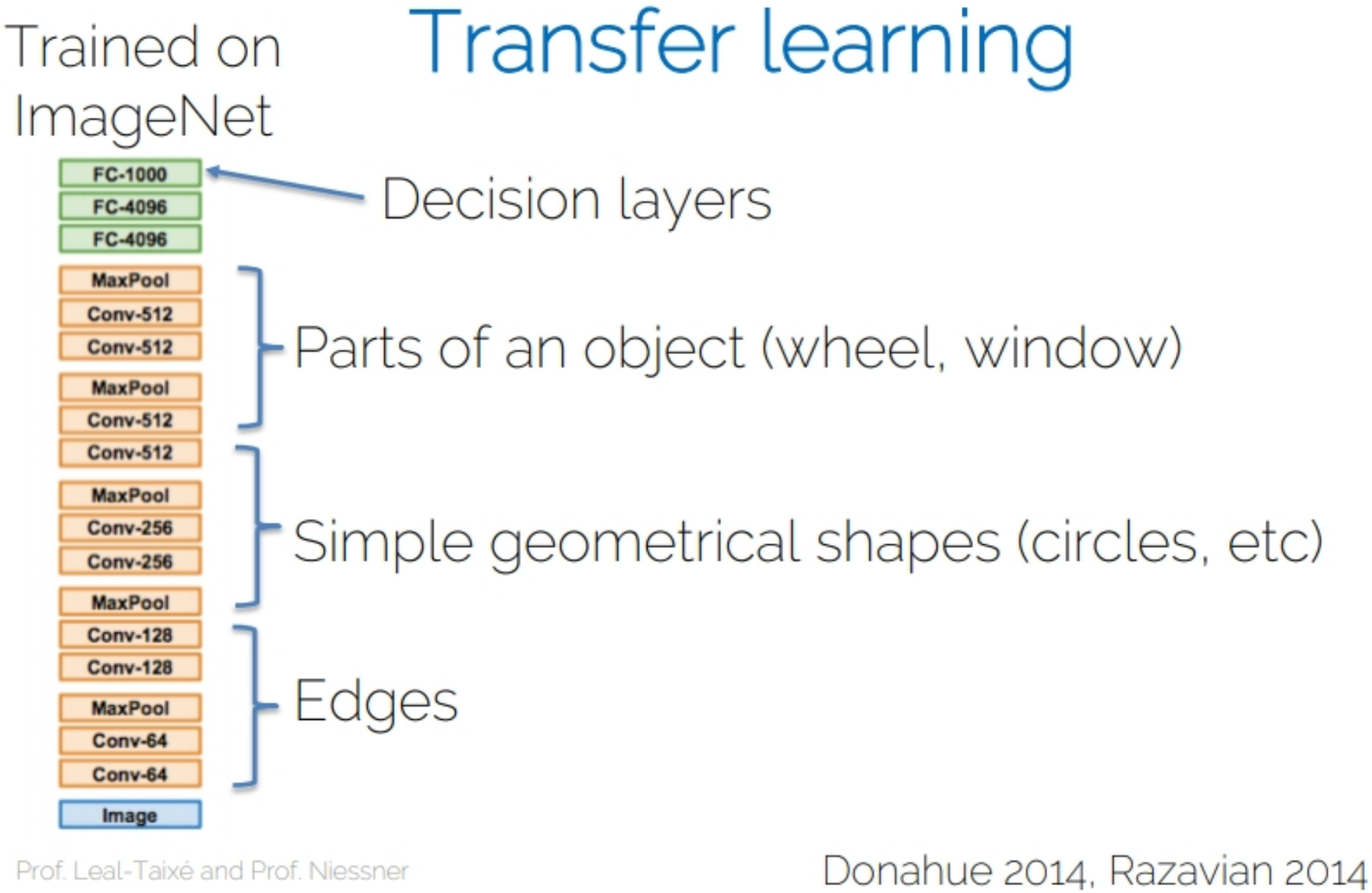
DEEP LEARNING WITH PYTORCH

Transfer learning

DEEP LEARNING WITH PYTORCH

Ismail Elezi
Ph.D. Student of Deep Learning

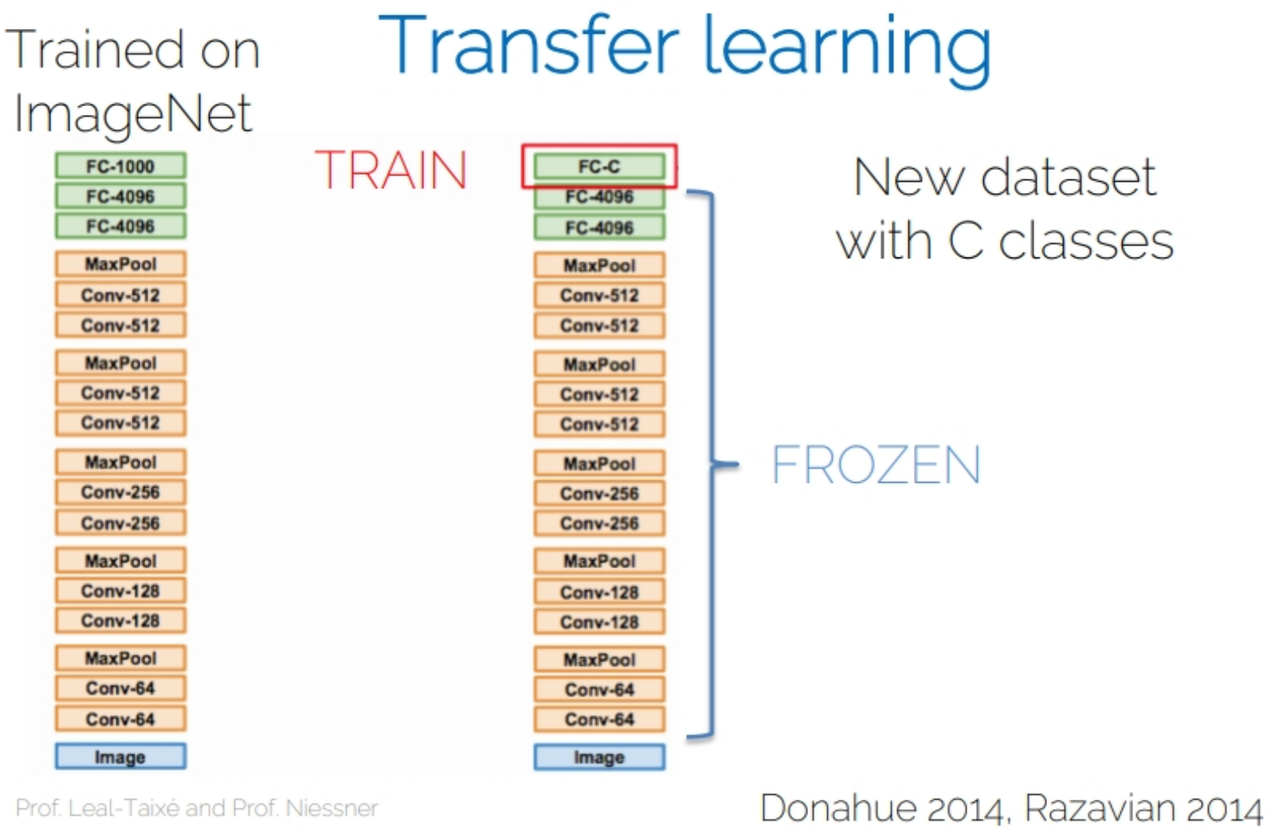
Features in CNN



Prof. Leal-Taixé and Prof. Niessner

Donahue 2014, Razavian 2014

Transfer Learning



Finetuning in PyTorch

```
# Instantiate the model
model = Net()

# Load the parameters from the old model
model.load_state_dict(torch.load('cifar10_net.pth'))

# Change the number of out channels
model.fc = nn.Linear(4 * 4 * 1024, 100)

# Train and evaluate the model
model.train()
```

Freezing the layers

```
# Instantiate the model
model = Net()

# Load the parameters from the old model
model.load_state_dict(torch.load('cifar10_net.pth'))

# Freeze all the layers bar the final one
for param in model.parameters():
    param.requires_grad = False

# Change the number of output units
model.fc = nn.Linear(4 * 4 * 1024, 100)

# Train and evaluate the model
model.train()
```

Torchvision library

```
import torchvision

model = torchvision.models.resnet18(pretrained=True)

model.fc = nn.Linear(512, num_classes)
```

Let's practice!

DEEP LEARNING WITH PYTORCH

Congratulations!

DEEP LEARNING WITH PYTORCH

Ismail Elezi
Ph.D. Student of Deep Learning

What you have learned

- Differences between neural networks and other types of classifiers.
- Building, training and testing basic neural networks.
- Building, training, testing and using convolutional neural networks.
- Detecting and preventing overfitting.
- Using the finetuning technique.
- Using the torchvision module to use pre-trained networks.

Thank you!

DEEP LEARNING WITH PYTORCH