Activation functions

INTRODUCTION TO DEEP LEARNING WITH PYTORCH

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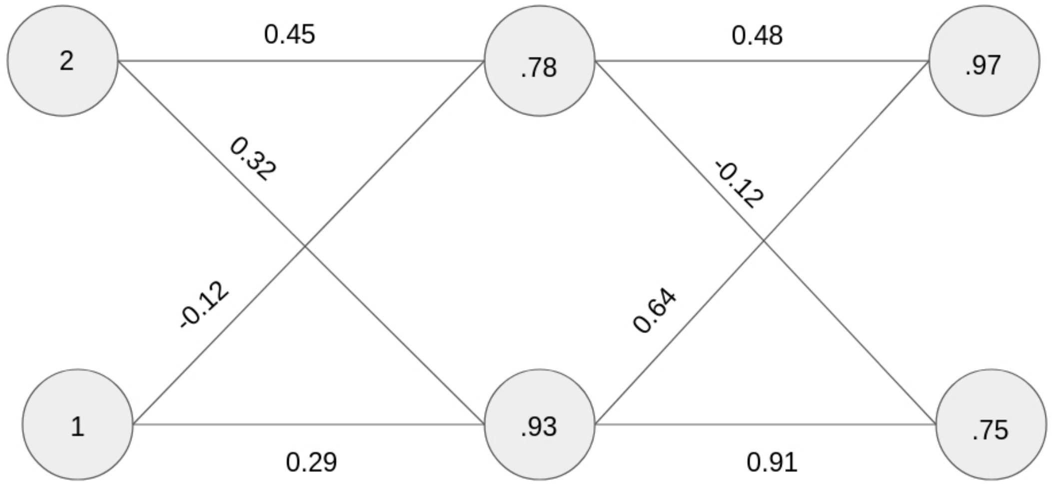
Motivation



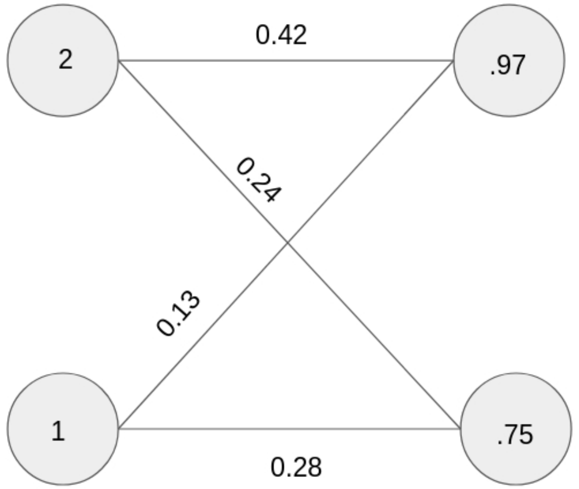

```
input_layer = torch.tensor([2., 1.])
weight_1 = torch.tensor([[0.45, 0.32], [-0.12, 0.29]])
hidden_layer = torch.matmul(input_layer, weight_1)
weight_2 = torch.tensor([[0.48, -0.12], [0.64, 0.91]])
output_layer = torch.matmul(hidden_layer, weight_2)
print(output_layer)
```

```
tensor([ 0.9696,  0.7527])
```

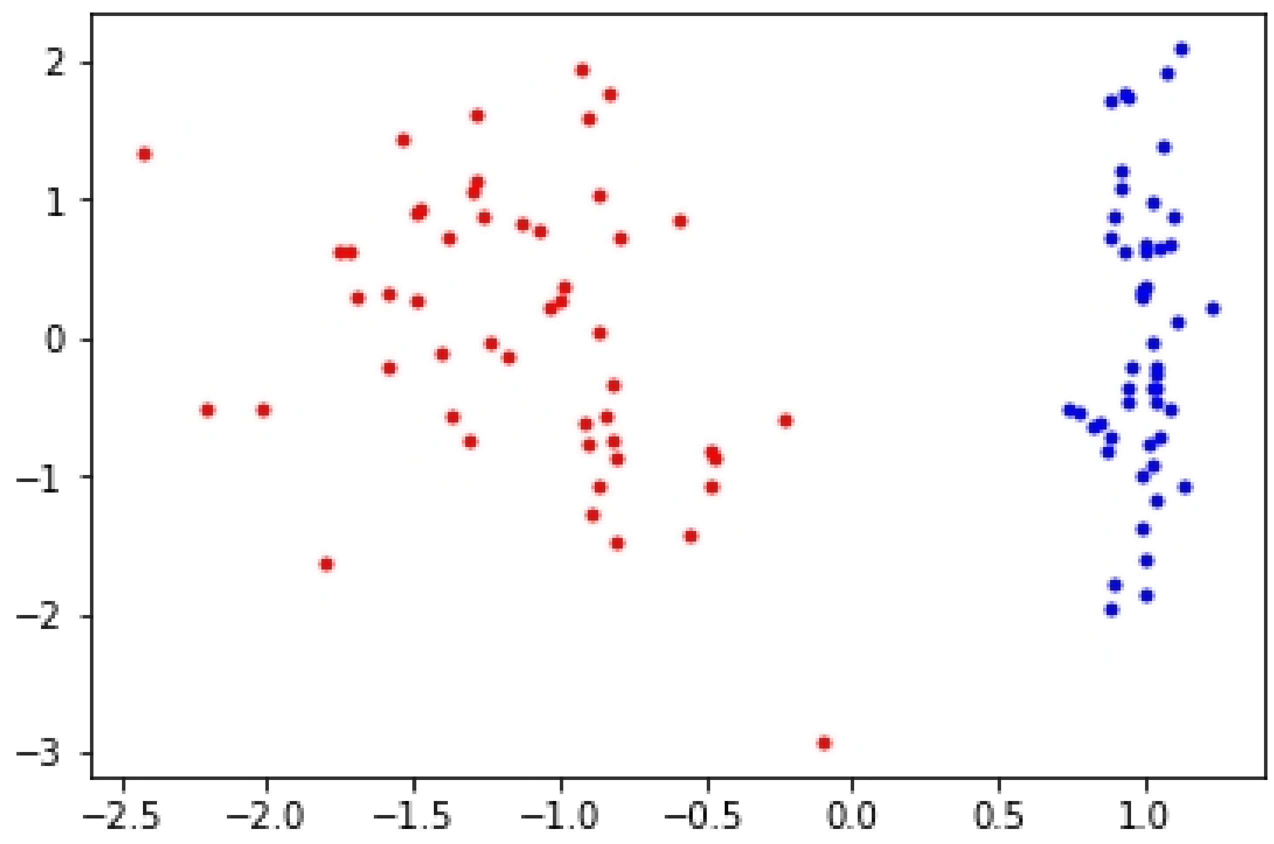
Matrix multiplication is a linear transformation

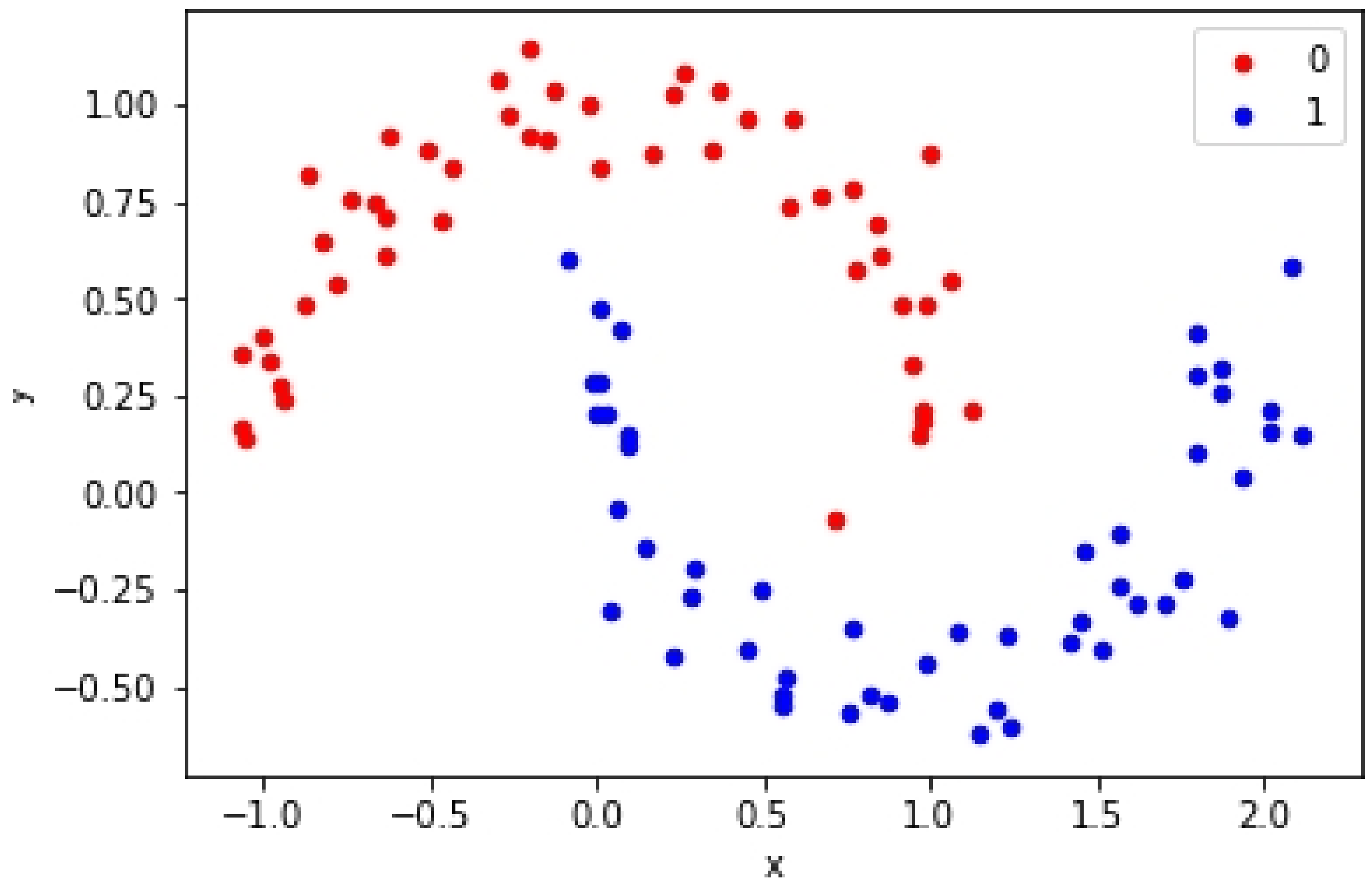
```
input_layer = torch.tensor([2., 1.])
weight_1 = torch.tensor([[0.45, 0.32], [-0.12, 0.29]])
weight_2 = torch.tensor([[0.48, -0.12], [0.64, 0.91]])
weight = torch.matmul(weight_1, weight_2)
output_layer = torch.matmul(input_layer, weight)
print(output_layer)
print(weight)
```

```
tensor([ 0.9696,  0.7527])
tensor([[ 0.4208,  0.2372], [ 0.1280,  0.2783]])
```



Non linearly separable datasets

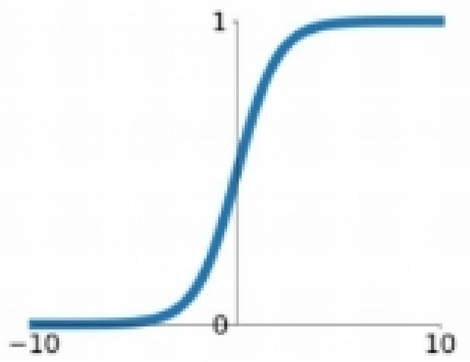




Activation functions

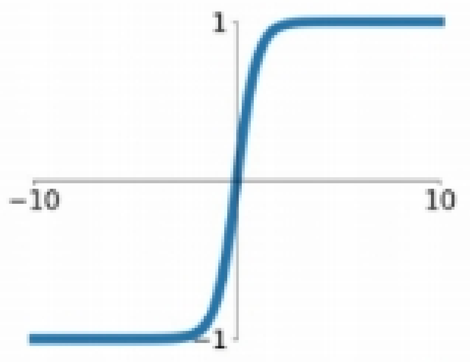
Sigmoid

$\sigma(x) = \frac{1}{1+e^{-x}}$



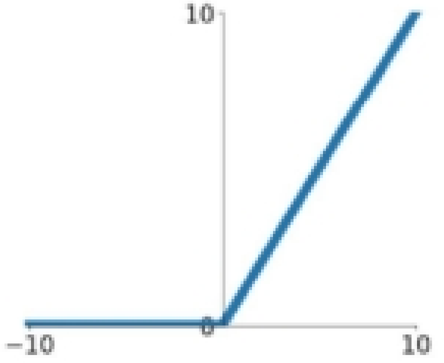
tanh

$\tanh(x)$



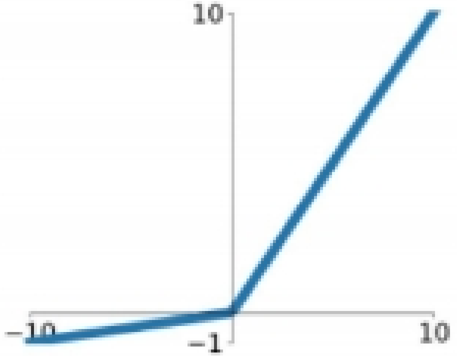
ReLU

$\max(0, x)$



Leaky ReLU

$\max(0.1x, x)$

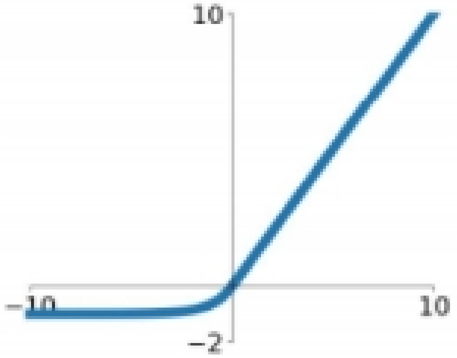


Maxout

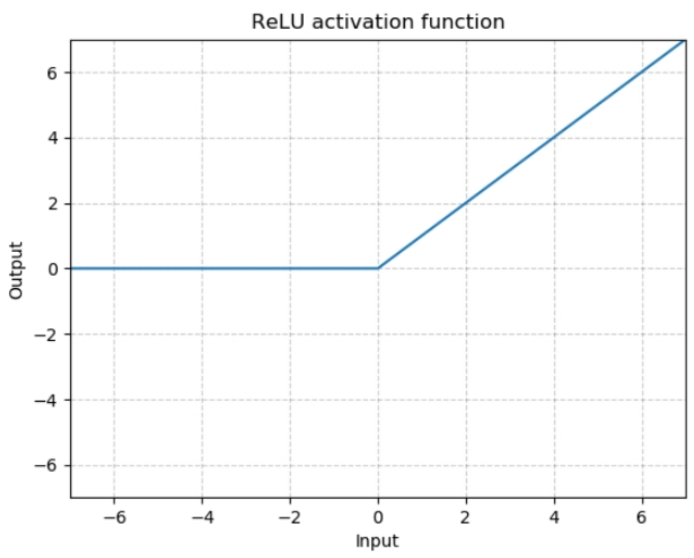
$\max(w_1^T x + b_1, w_2^T x + b_2)$

ELU

$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$



ReLU activation function




```
ReLU(x) = max(0, x)
```

```python
import torch.nn as nn
relu = nn.ReLU()

tensor_1 = torch.tensor([2., -4.])
print(relu(tensor_1))

tensor_2 = torch.tensor([[2., -4.],
                         [1.2, 0.]])
print(relu(tensor_2))
```

```
tensor([ 2.,  0.])


tensor([[ 2.0000,  0.0000],
        [ 1.2000,  0.0000]])
```

Let us implement some activation functions

INTRODUCTION TO DEEP LEARNING WITH PYTORCH

Loss functions

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Loss Functions

- Initialize neural networks with random weights.
- Do a forward pass.
- Calculate loss function (1 number).
- Calculate the gradients.
- Change the weights based on gradients.

- For regression: least squared loss.
- For classification: softmax cross-entropy loss.
- For more complicated problems (like object detection), more complicated losses.

Softmax Cross-Entropy Loss

cat	**3.2**
car	5.1
frog	-1.7

$$P(Y = k | X = x_i) = \frac{e^{s_k}}{\sum_j e^{s_j}}$$

Softmax Function

Softmax Cross-Entropy Loss

Probabilities must be >= 0

cat	**3.2**		**24.5**
car	5.1	$\xrightarrow{\text{exp}}$	164.0
frog	-1.7		0.18

unnormalized probabilities

$$P(Y = k | X = x_i) = \frac{e^{s_k}}{\sum_j e^{s_j}}$$ Softmax Function

Softmax Cross-Entropy Loss

$$P(Y = k | X = x_i) = \frac{e^{s_k}}{\sum_j e^{s_j}}$$

Softmax Function

Probabilities must be >= 0

Probabilities must sum to 1

			$\xrightarrow{\text{exp}}$		$\xrightarrow{\text{normalize}}$	
cat	**3.2**			**24.5**		**0.13**
car	5.1			164.0		0.87
frog	-1.7			0.18		0.00

unnormalized probabilities

probabilities

Softmax Cross-Entropy Loss

$$P(Y = k | X = x_i) = \frac{e^{s_k}}{\sum_j e^{s_j}}$$ Softmax Function

			Probabilities must be >= 0		Probabilities must sum to 1
cat	**3.2**		**24.5**		**0.13**
car	5.1	exp →	164.0	normalize →	0.87
frog	-1.7		0.18		0.00
			unnormalized probabilities		probabilities

L = - ln(0.13) = 2.0404

CE loss in PyTorch

```
logits = torch.tensor([[3.2, 5.1, -1.7]])
ground_truth = torch.tensor([0])
criterion = nn.CrossEntropyLoss()

loss = criterion(logits, ground_truth)
print(loss)
```

```
tensor(2.0404)
```

CE loss in PyTorch

```
logits = torch.tensor([[10.2, 5.1, -1.7]])
loss = criterion(logits, ground_truth)
print(loss)
```

```
tensor(0.0061)
```

```
logits = torch.tensor([[-10, 5.1, -1.7]])
loss = criterion(logits, ground_truth)
print(loss)
```

```
tensor(15.1011)
```

Let's practice!

INTRODUCTION TO DEEP LEARNING WITH PYTORCH

Preparing a dataset in PyTorch

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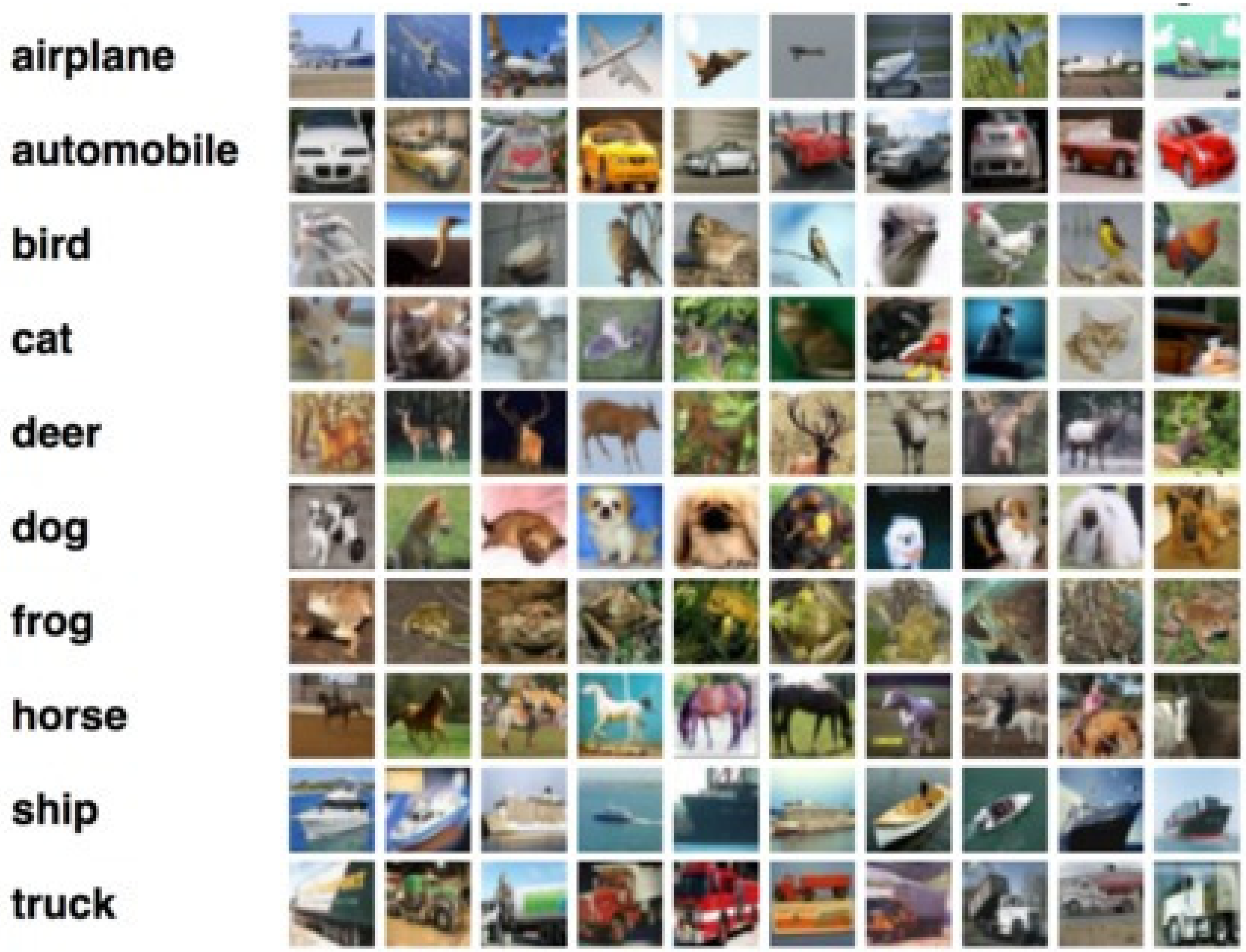
MNIST and CIFAR-10



Datasets and Dataloaders

```
import torch
import torchvision
import torch.utils.data
import torchvision.transforms as transforms
transform = transforms.Compose(
    [transforms.ToTensor(),
     transforms.Normalize((0.4914, 0.48216, 0.44653),
                          (0.24703, 0.24349, 0.26159))])
```

Datasets and Dataloaders

```
trainset = torchvision.datasets.CIFAR10(root='./data', train=True,
                                        download=True, transform=transform)

testset = torchvision.datasets.CIFAR10(root='./data', train=False,
                                       download=True, transform=transform)
trainloader = torch.utils.data.DataLoader(trainset, batch_size=32,
                                          shuffle=True, num_workers=4)

testloader = torch.utils.data.DataLoader(testset, batch_size=32,
                                         shuffle=False, num_workers=4)
```

Inspecting the dataloader

```
print(testloader.dataset.test_data.shape, trainloader.dataset.train_data.shape)
```

```
(10000, 32, 32, 3), (50000, 32, 32, 3)
```

```
print(testloader.batch_size)
```

```
32
```

```
print(trainloader.sampler)
```

```
<torch.utils.data.sampler.RandomSampler object at 0x7f0612fb85c0>
```

Let's practice!

INTRODUCTION TO DEEP LEARNING WITH PYTORCH

Training neural networks

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Recipe for training neural networks

- Prepare the dataloaders.
- Build a neural network.

Loop over:

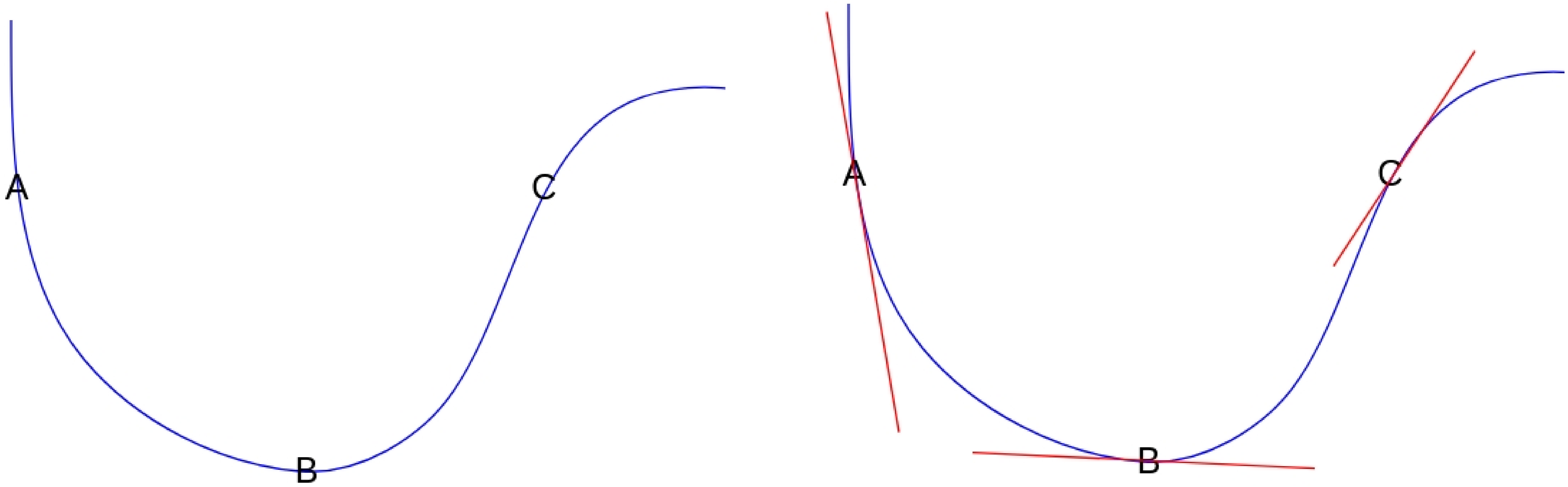
- Do a forward pass.
- Calculate loss function (1 number).
- Calculate the gradients.
- Change the weights based on gradients.

- Lesson 2.3.
- Lesson 1.4 and Lesson 2.1.

Loop over:

- Lesson 1.2.
- Lesson 2.2.
- Lesson 1.3.
- weight -= weight_gradient * learning_rate.

Gradient descent



Recap - Dataloaders

```
import torch
import torchvision
import torch.utils.data
import torchvision.transforms as transforms

transform = transforms.Compose(
    [transforms.ToTensor(),
     transforms.Normalize((0.4914, 0.48216, 0.44653),
                          (0.24703, 0.24349, 0.26159))])

trainset = torchvision.datasets.CIFAR10(root='./data', train=True,
                                        download=True, transform=transform)

testset = torchvision.datasets.CIFAR10(root='./data', train=False,
                                       download=True, transform=transform)

trainloader = torch.utils.data.DataLoader(trainset, batch_size=32
```

Neural Networks - Recap

```
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim

class Net(nn.Module):
    def __init__(self):
        super(Net, self).__init__()
        self.fc1 = nn.Linear(32 * 32 * 3, 500)
        self.fc2 = nn.Linear(500, 10)

    def forward(self, x):
        x = F.relu(self.fc1(x))
        return self.fc2(x)
```

Training the Neural Network

```
net = Net()
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(net.parameters(), lr=3e-4)

for epoch in range(10):  # loop over the dataset multiple times
    for i, data in enumerate(trainloader, 0):
        # Get the inputs
        inputs, labels = data
        inputs = inputs.view(-1, 32 * 32 * 3)

        # Zero the parameter gradients
        optimizer.zero_grad()

        # Forward + backward + optimize
        outputs = net(inputs)
        loss = criterion(outputs, labels)
        loss.backward()
        optimizer.step()
```

Using the net to get predictions

```
correct, total = 0, 0
predictions = []
net.eval()
for i, data in enumerate(testloader, 0):
    inputs, labels = data
    inputs = inputs.view(-1, 32*32*3)
    outputs = net(inputs)
    _, predicted = torch.max(outputs.data, 1)
    predictions.append(outputs)
    total += labels.size(0)
    correct += (predicted == labels).sum().item()

print('The testing set accuracy of the network is: %d %%' % (100 * correct / total))
```

```
The testing set accuracy of the network is: 53 %
```

Let's practice!

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