

# Introduction to PyTorch

INTRODUCTION TO DEEP LEARNING WITH PYTORCH



Ismail Elezi

Ph.D. Student of Deep Learning

airplane

automobile

bird

cat

deer

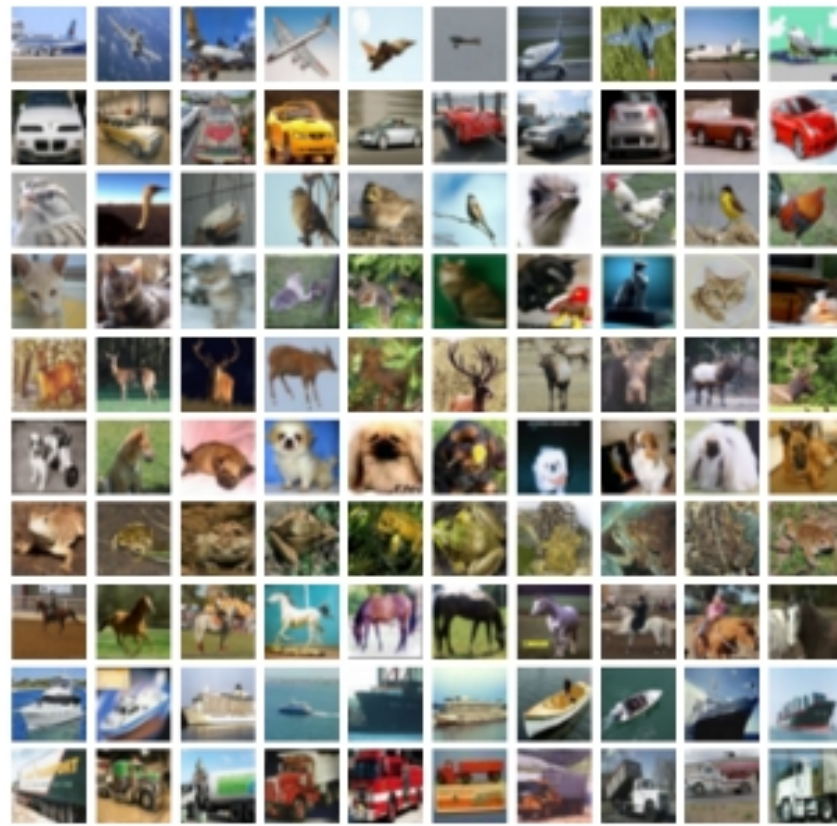
dog

frog

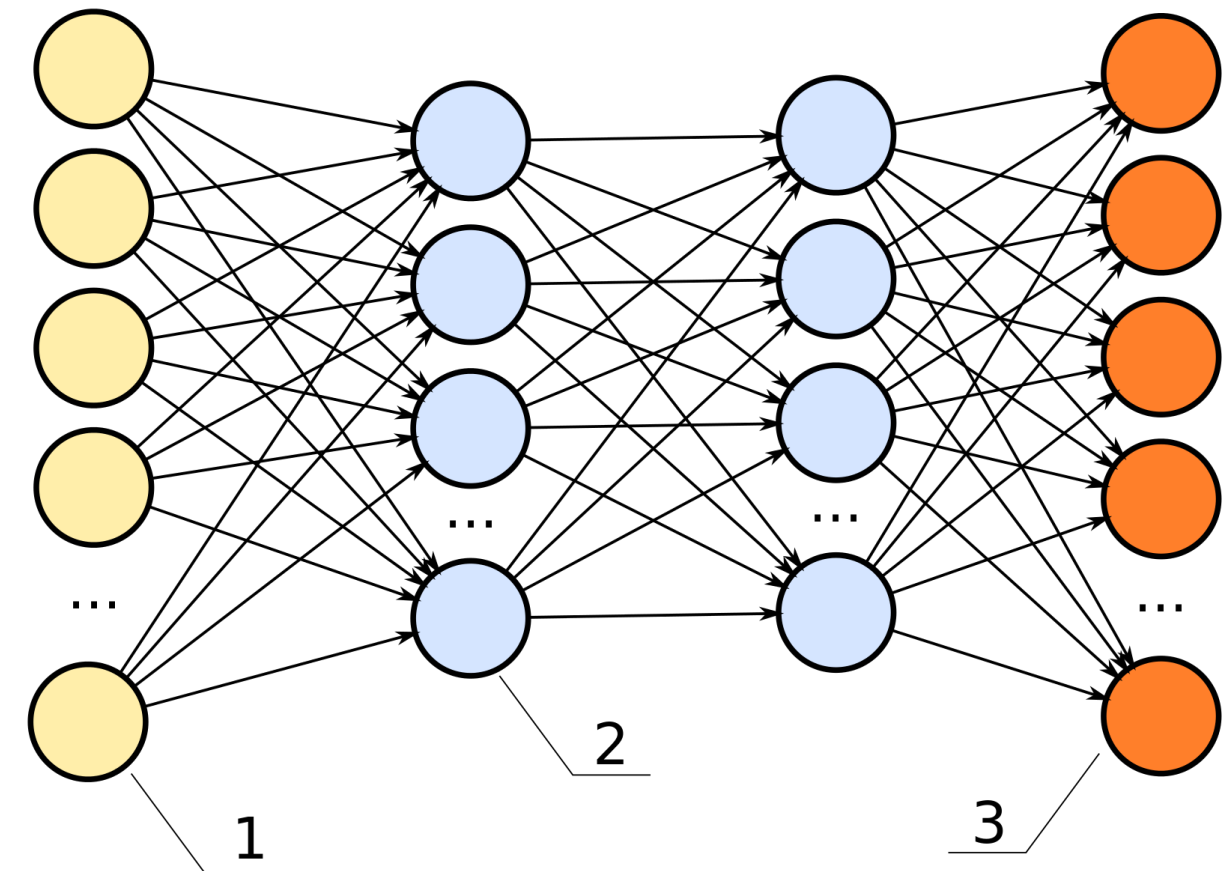
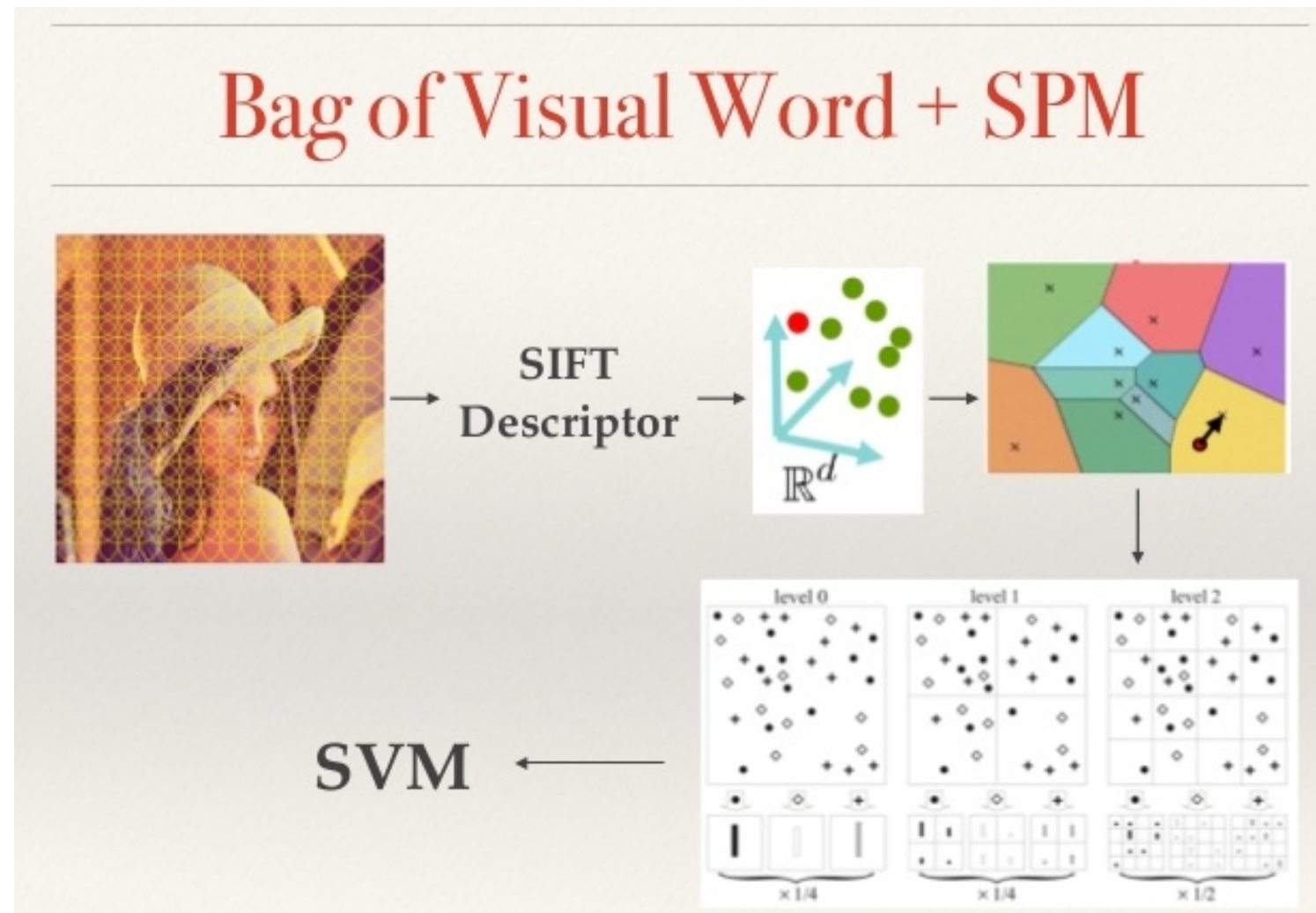
horse

ship

truck



# Neural networks





# Why PyTorch?



- "PyThonic" - easy to use
- Strong GPU support - models run fast
- Many algorithms are already implemented
- Automatic differentiation - more in next lesson
- Similar to NumPy

# Matrix Multiplication

"Dot Product"

$$\begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{bmatrix} \times \begin{bmatrix} 7 & 8 \\ 9 & 10 \\ 11 & 12 \end{bmatrix} = \begin{bmatrix} 58 & \phantom{00} \end{bmatrix}$$

# PyTorch compared to NumPy

```
import torch
torch.tensor([[2, 3, 5], [1, 2, 9]])
```

```
tensor([[ 2,  3,  5],
        [ 1,  2,  9]])
```

```
torch.rand(2, 2)
```

```
tensor([[ 0.0374, -0.0936],
        [ 0.3135, -0.6961]])
```

```
a = torch.rand((3, 5))
a.shape
```

```
torch.Size([3, 5])
```

```
import numpy as np
np.array([[2, 3, 5], [1, 2, 9]])
```

```
array([[ 2,  3,  5],
        [ 1,  2,  9]])
```

```
np.random.rand(2, 2)
```

```
array([[ 0.0374, -0.0936],
        [ 0.3135, -0.6961]])
```

```
a = np.random.randn(3, 5)
a.shape
```

```
(3, 5)
```

# Matrix operations

```
a = torch.rand((2, 2))  
b = torch.rand((2, 2))
```

```
tensor([[ -0.6110,  0.0145],  
        [ 1.3583, -0.0921]])  
tensor([[ 0.0673,  0.6419],  
        [-0.0734,  0.3283]])
```

```
torch.matmul(a, b)
```

```
tensor([[ -0.0422, -0.3875],  
        [ 0.0981,  0.8417]])
```

```
a = np.random.rand(2, 2)  
b = np.random.rand(2, 2)
```

```
array([[ -0.6110,  0.0145],  
       [ 1.3583, -0.0921]])  
array([[ 0.0673,  0.6419],  
       [-0.0734,  0.3283]])
```

```
np.dot(a, b)
```

```
array([[ -0.0422, -0.3875],  
       [ 0.0981,  0.8417]])
```

# Matrix operations

```
a * b
```

```
tensor([[ -0.0411,  0.0093],  
        [ -0.0998, -0.0302]])
```

```
np.multiply(a, b)
```

```
array([[ -0.0411,  0.0093],  
       [ -0.0998, -0.0302]])
```



# Zeros and Ones

```
a_torch = torch.zeros(2, 2)
```

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

```
b_torch = torch.ones(2, 2)
```

```
tensor([[1., 1.],  
        [1., 1.]])
```

```
c_torch = torch.eye(2)
```

```
tensor([[1., 0.],  
        [0., 1.]])
```

```
a_numpy = np.zeros((2, 2))
```

```
array([[0., 0.],  
       [0., 0.]])
```

```
b_numpy = np.ones((2, 2))
```

```
array([[1., 1.],  
       [1., 1.]])
```

```
c_numpy = np.identity(2)
```

```
array([[1., 0.],  
       [0., 1.]])
```

# PyTorch to NumPy and vice versa

```
d_torch = torch.from_numpy(c_numpy)
```

```
tensor([[1., 0.],  
        [0., 1.],  
        dtype=torch.float64)
```

```
d = c_torch.numpy()
```

```
array([[1., 0.],  
       [0., 1.]])
```

# Summary

```
torch.matmul(a, b)    # multiplies torch tensors a and b

*                    # element-wise multiplication between two torch tensors

torch.eye(n)          # creates an identity torch tensor with shape (n, n)

torch.zeros(n, m)     # creates a torch tensor of zeros with shape (n, m)

torch.ones(n, m)      # creates a torch tensor of ones with shape (n, m)

torch.rand(n, m)      # creates a random torch tensor with shape (n, m)
```

# Let's practice

INTRODUCTION TO DEEP LEARNING WITH PYTORCH

# Forward propagation

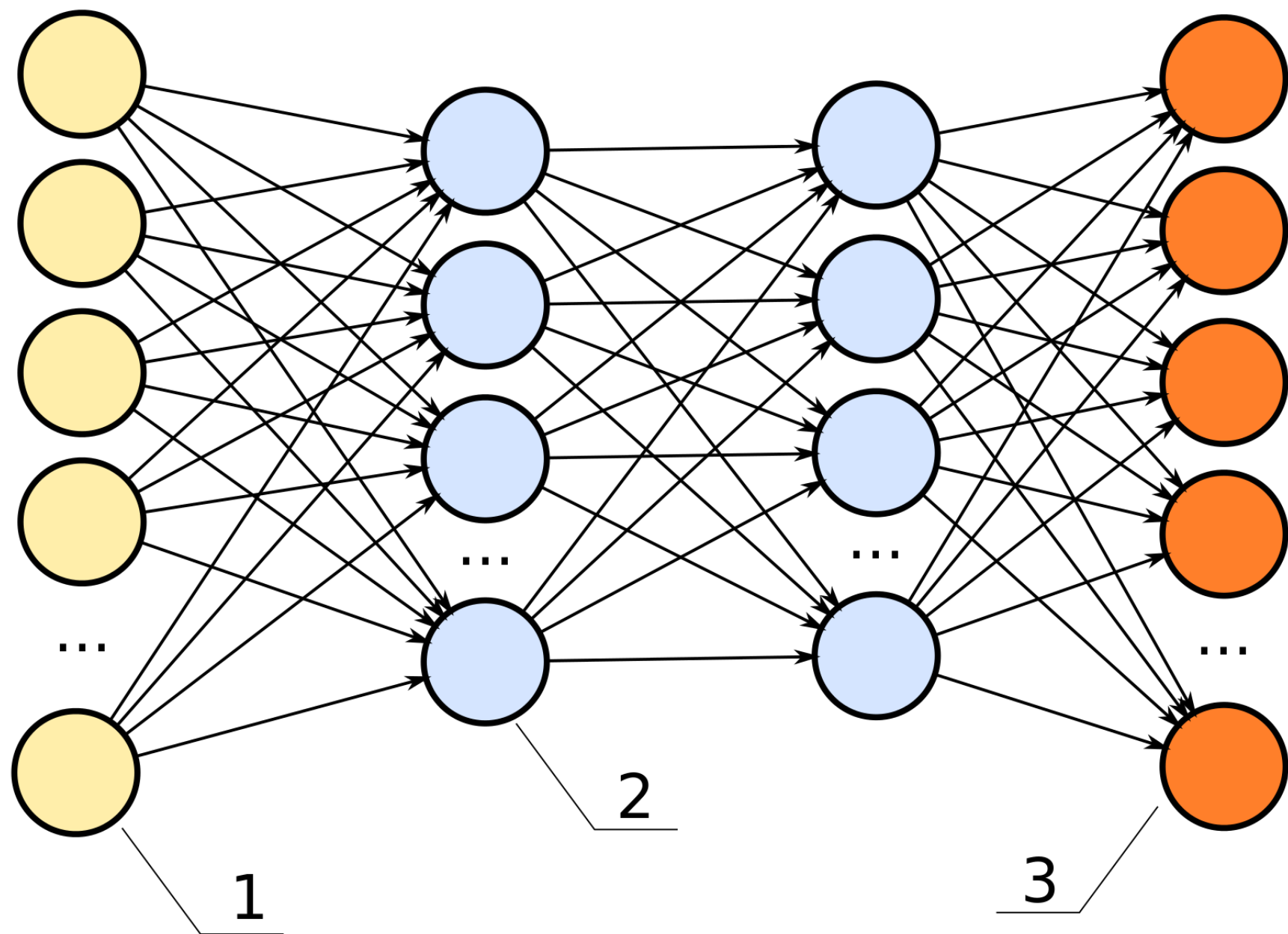
INTRODUCTION TO DEEP LEARNING WITH PYTORCH

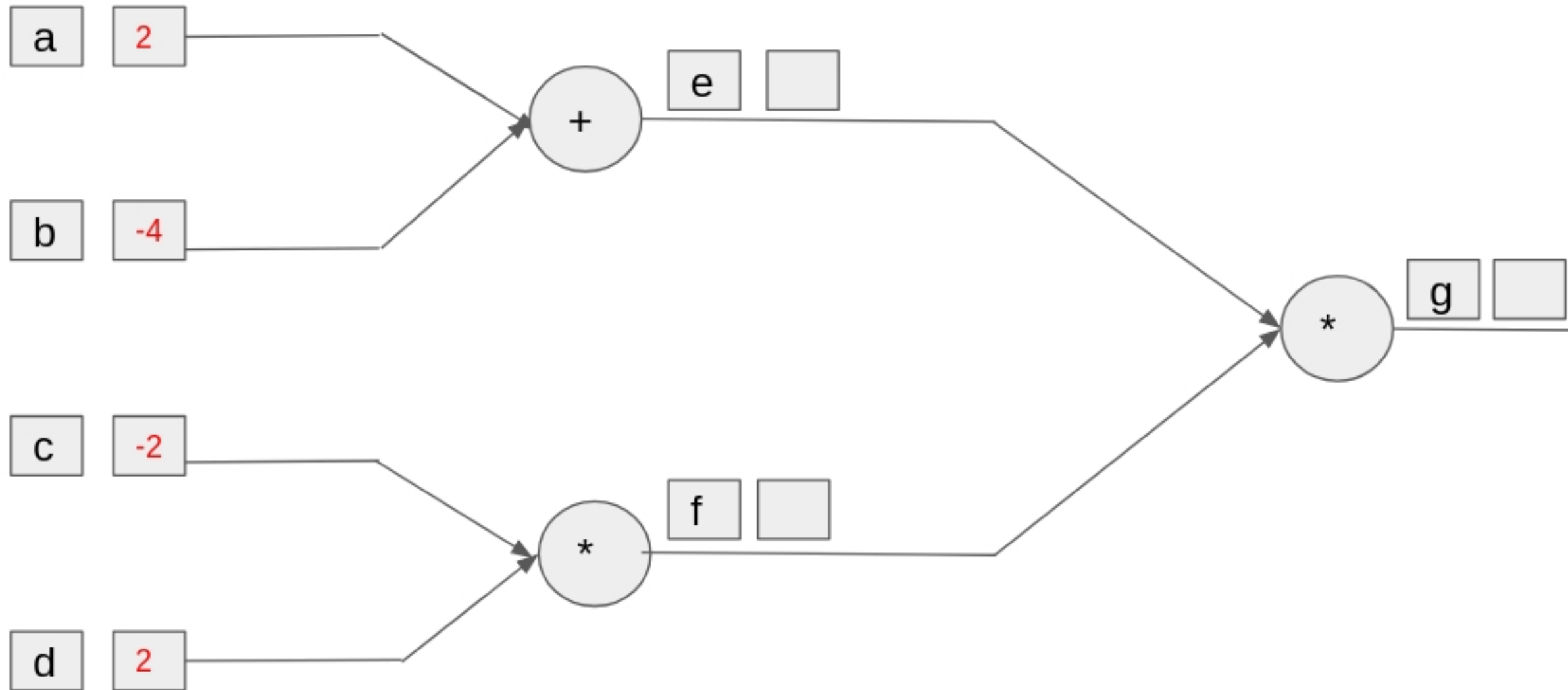


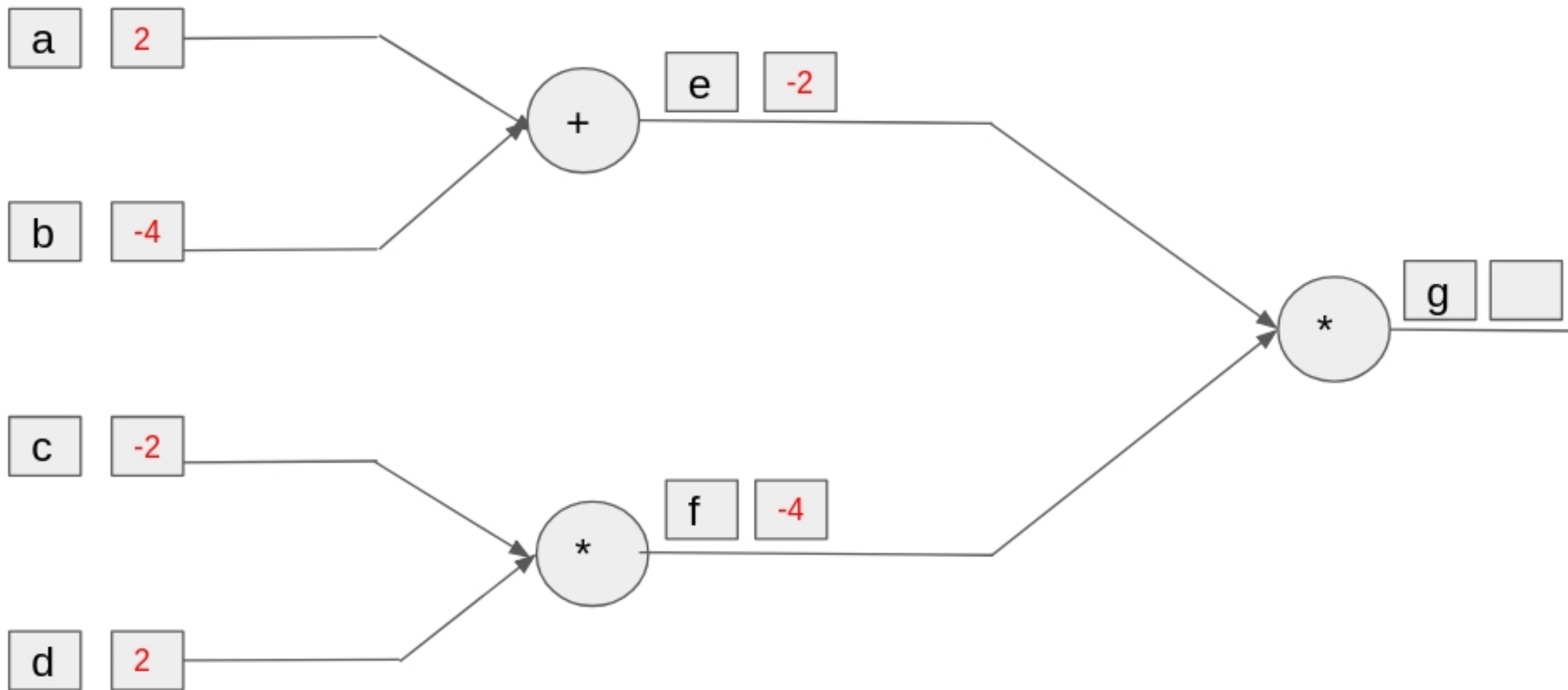
**Ismail Elezi**

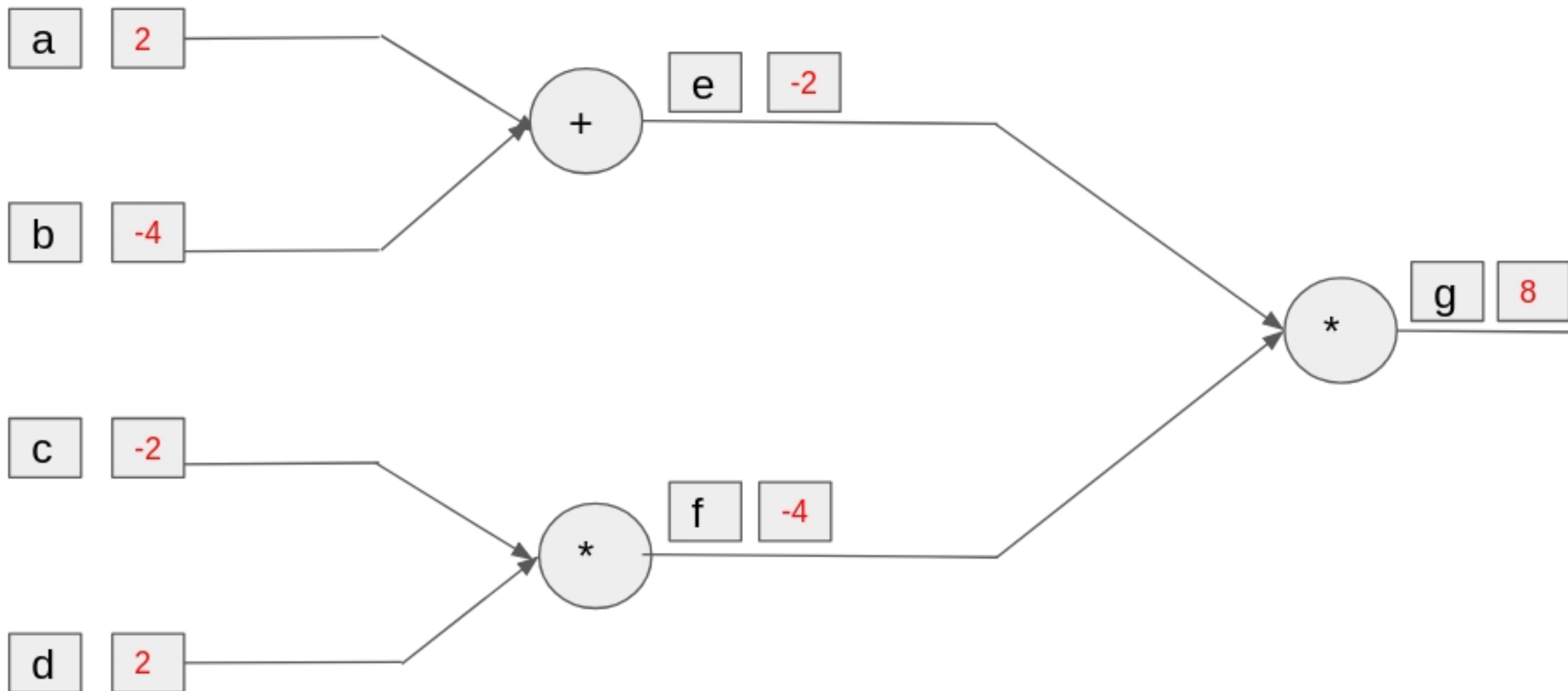
Ph.D. Student of Deep Learning











# PyTorch implementation

```
import torch
```

```
a = torch.Tensor([2])  
b = torch.Tensor([-4])  
c = torch.Tensor([-2])  
d = torch.Tensor([2])
```

```
e = a + b  
f = c * d
```

```
g = e * f  
print(e, f, g)
```

```
tensor([-2.]), tensor([-4.]), tensor([8.])
```



# Let's practice!

INTRODUCTION TO DEEP LEARNING WITH PYTORCH

# Backpropagation by auto-differentiation

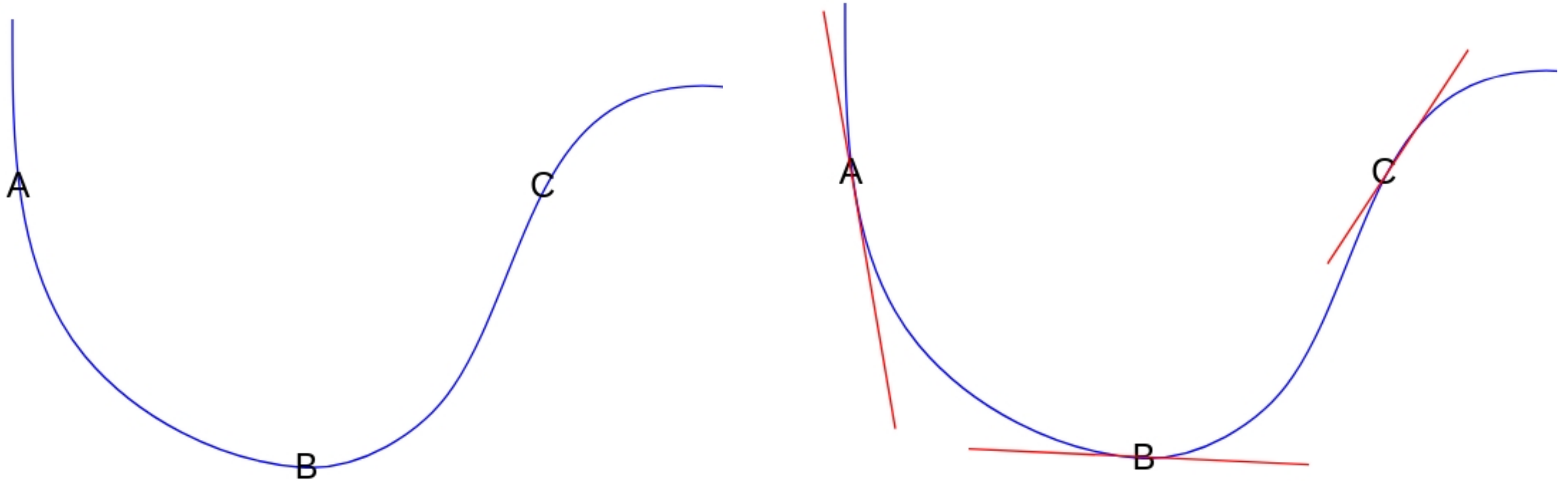
INTRODUCTION TO DEEP LEARNING WITH PYTORCH



Ismail Elezi

Ph.D. Student of Deep Learning

# Derivatives



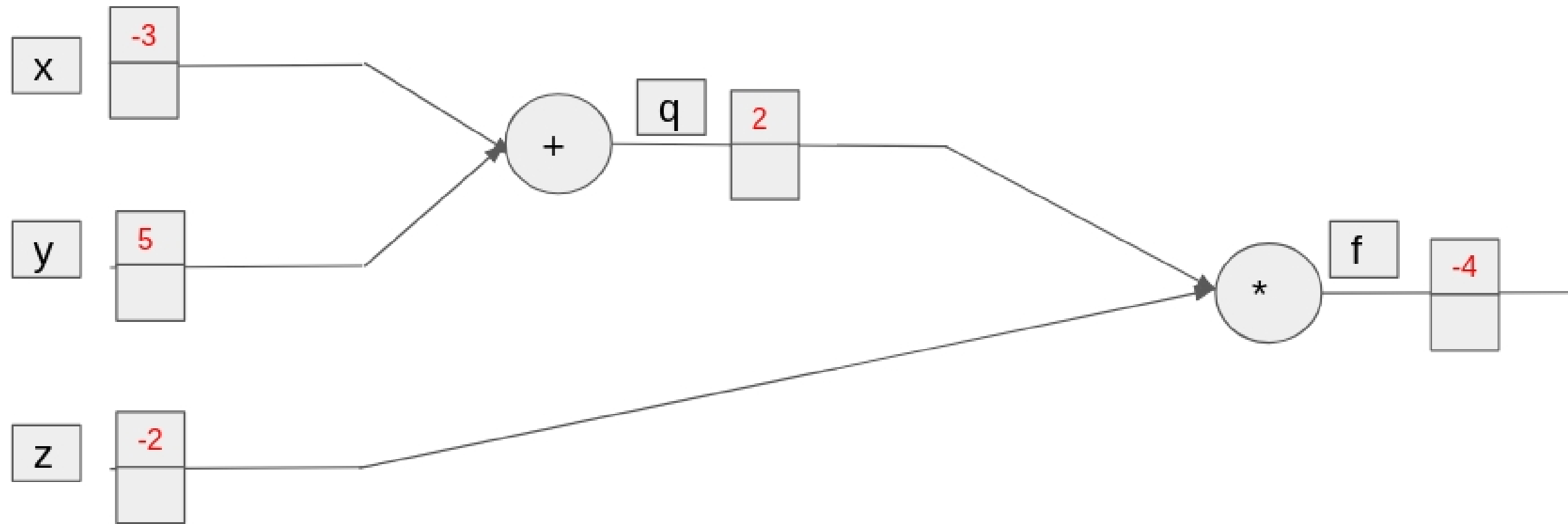
# Derivative Rules

Interaction	Overall Change
Addition	$(f + g)' = f' + g'$
Multiplication	$(f \cdot g)' = f \cdot dg + g \cdot df$
Powers	$(x^n)' = \frac{d}{dx} x^n = nx^{n-1}$
Inverse	$\left(\frac{1}{x}\right)' = -\frac{1}{x^2}$
Division	$\left(\frac{f}{g}\right)' = \left(df \cdot \frac{1}{g}\right) + \left(\frac{-1}{g^2} dg \cdot f\right)$

$$\frac{d}{dx} \left[ (f(x))^n \right] = n(f(x))^{n-1} \cdot f'(x)$$

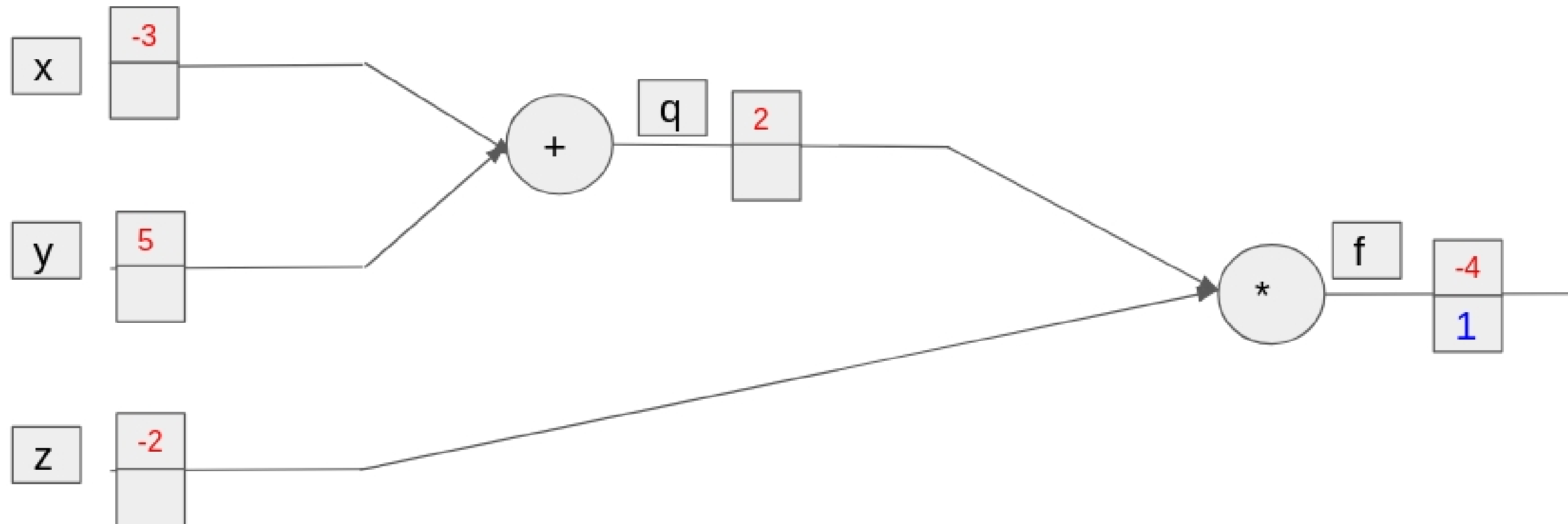
$$\frac{d}{dx} [f(g(x))] = f'(g(x))g'(x)$$

# Derivative Example - Forward Pass

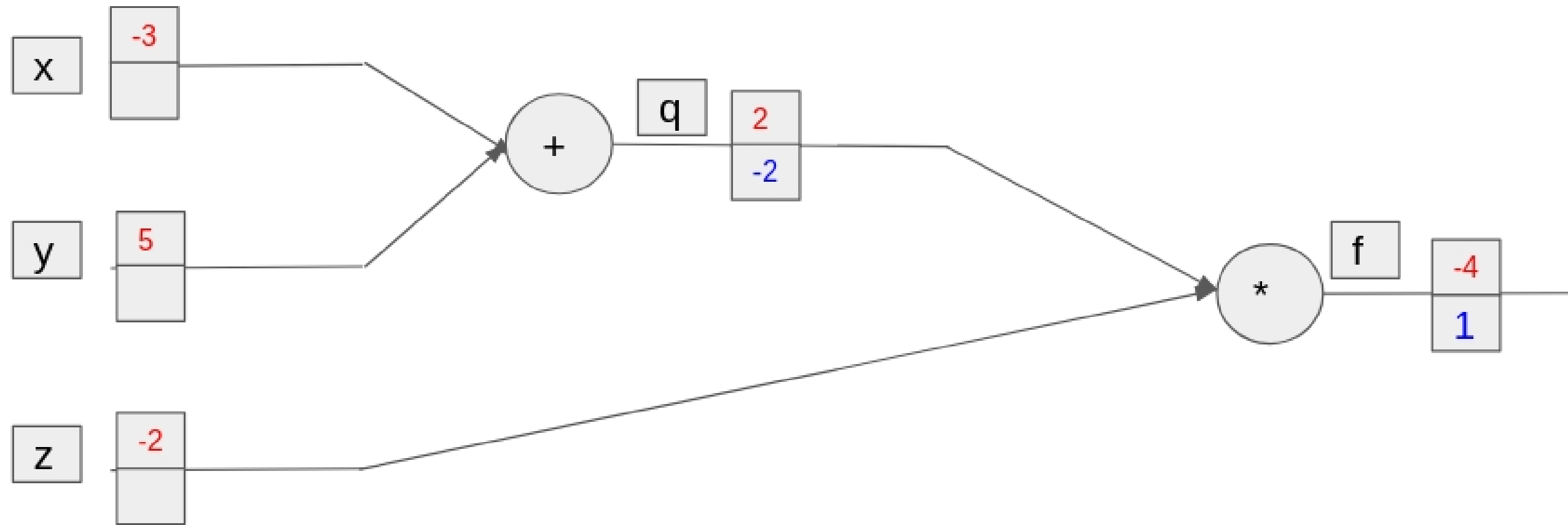




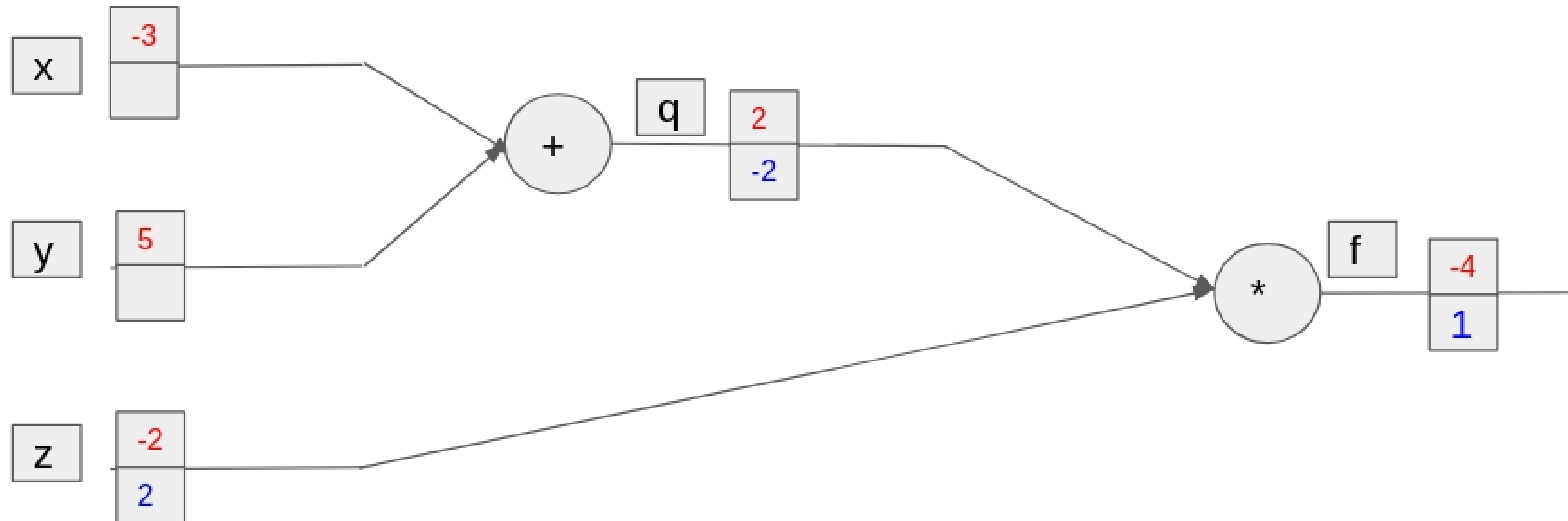
# Derivative Example - Backward Pass



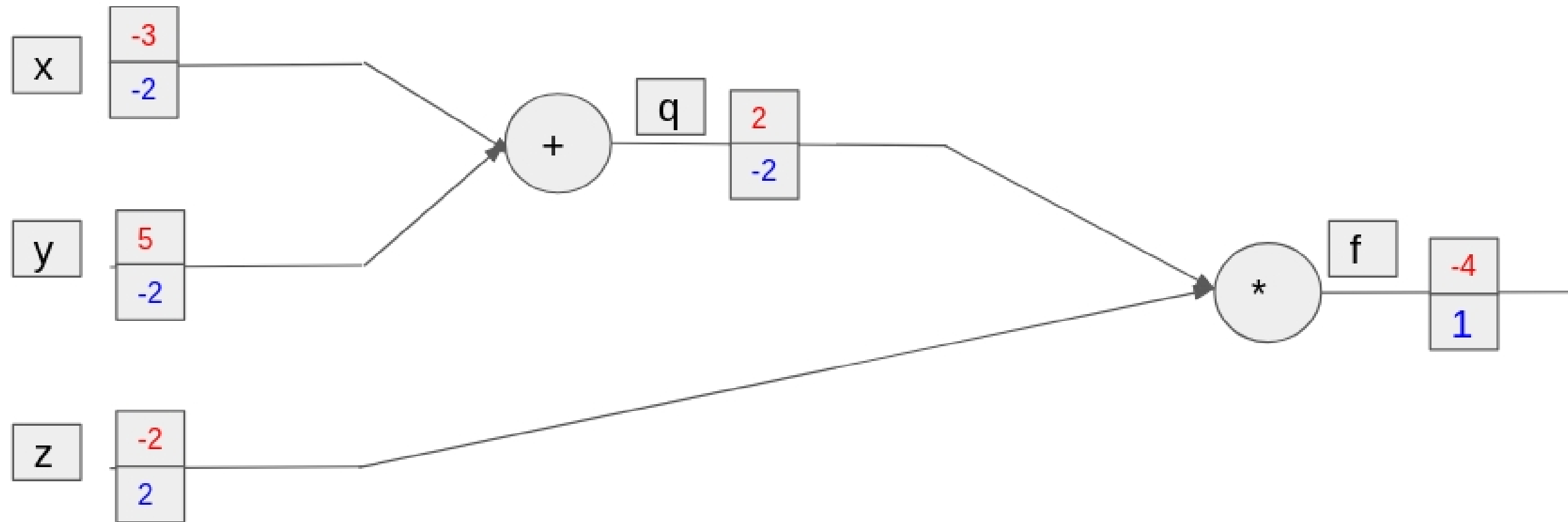
# Derivative Example - Backward Pass



# Derivative Example - Backward Pass



# Derivative Example - Backward Pass



# Backpropagation in PyTorch

```
import torch

x = torch.tensor(-3., requires_grad=True)
y = torch.tensor(5., requires_grad=True)
z = torch.tensor(-2., requires_grad=True)

q = x + y
f = q * z

f.backward()

print("Gradient of z is: " + str(z.grad))
print("Gradient of y is: " + str(y.grad))
print("Gradient of x is: " + str(x.grad))
```

```
Gradient of z is: tensor(2.)
Gradient of y is: tensor(-2.)
Gradient of x is: tensor(-2.)
```



# Let's practice

INTRODUCTION TO DEEP LEARNING WITH PYTORCH

# Introduction to Neural Networks

INTRODUCTION TO DEEP LEARNING WITH PYTORCH

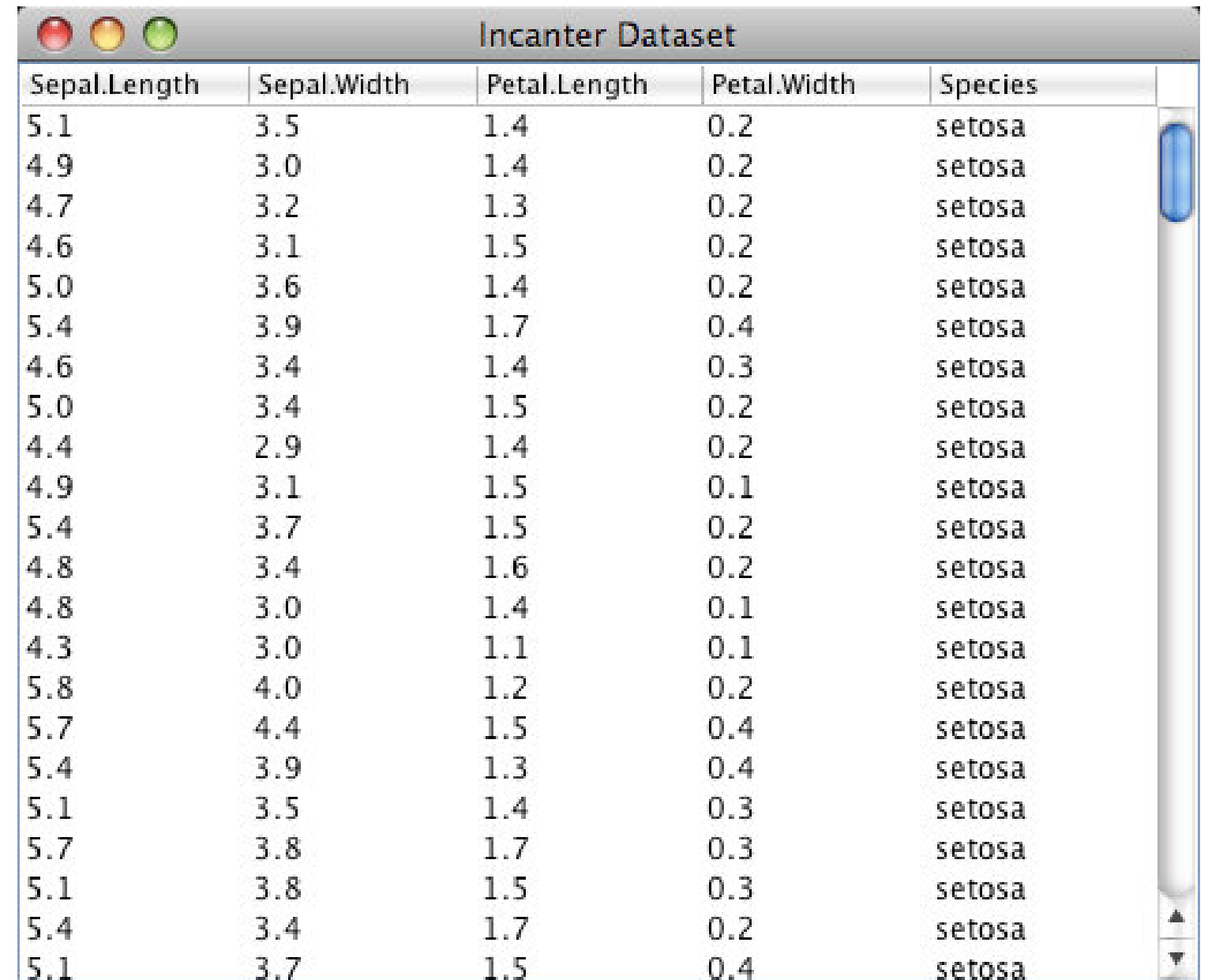


Ismail Elezi

Ph.D. Student of Deep Learning

# Other classifiers

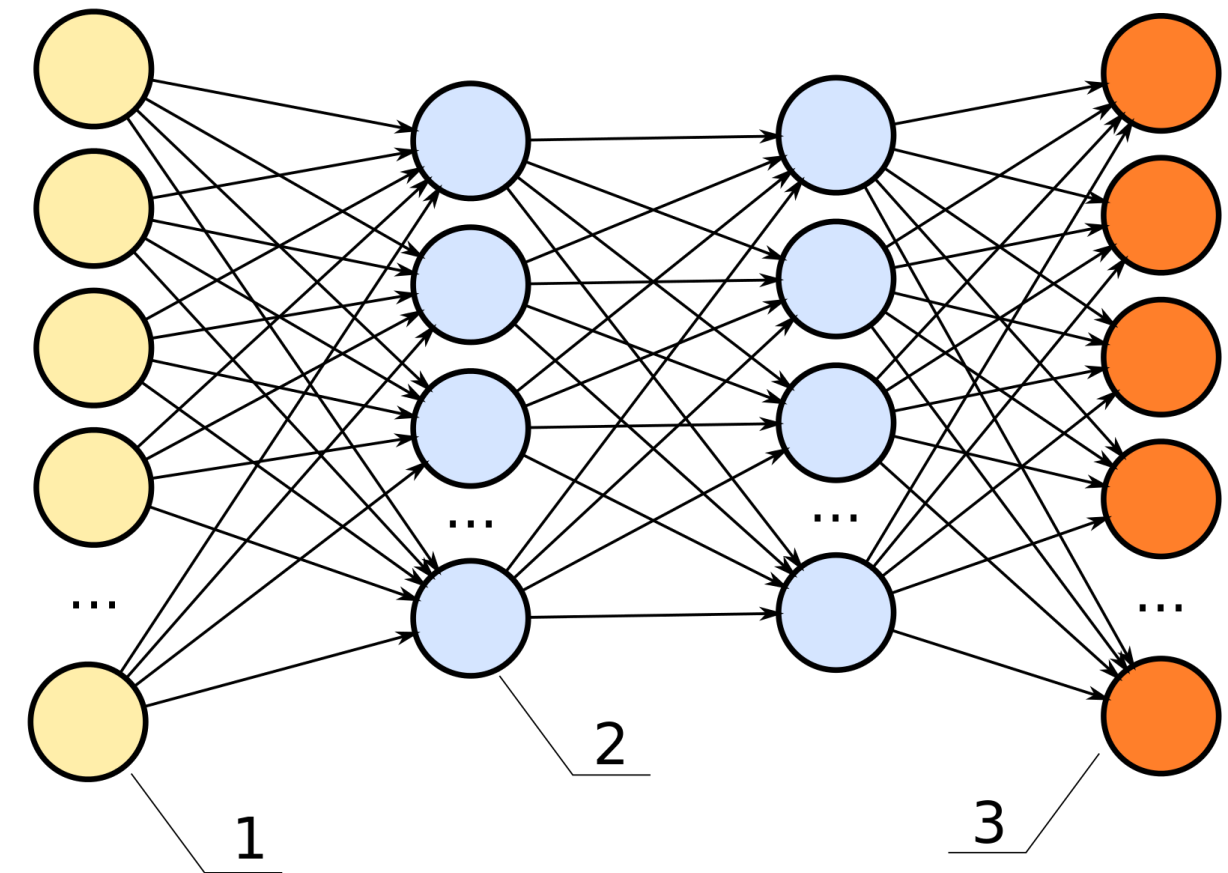
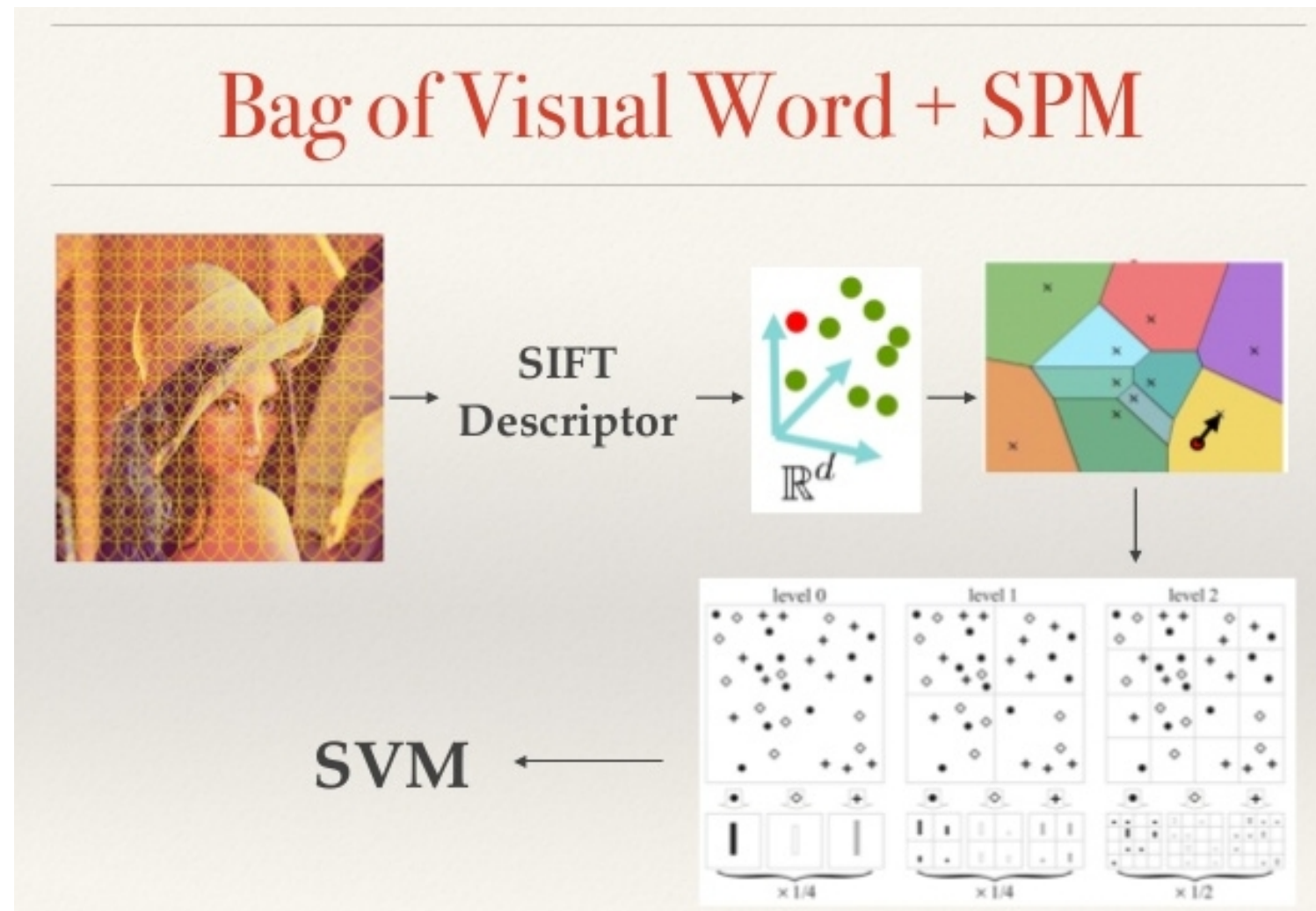
- k-Nearest Neighbour
- Logistic/Linear Regression
- Random Forests
- Gradient Boosted Trees
- Support Vector Machines
- ...



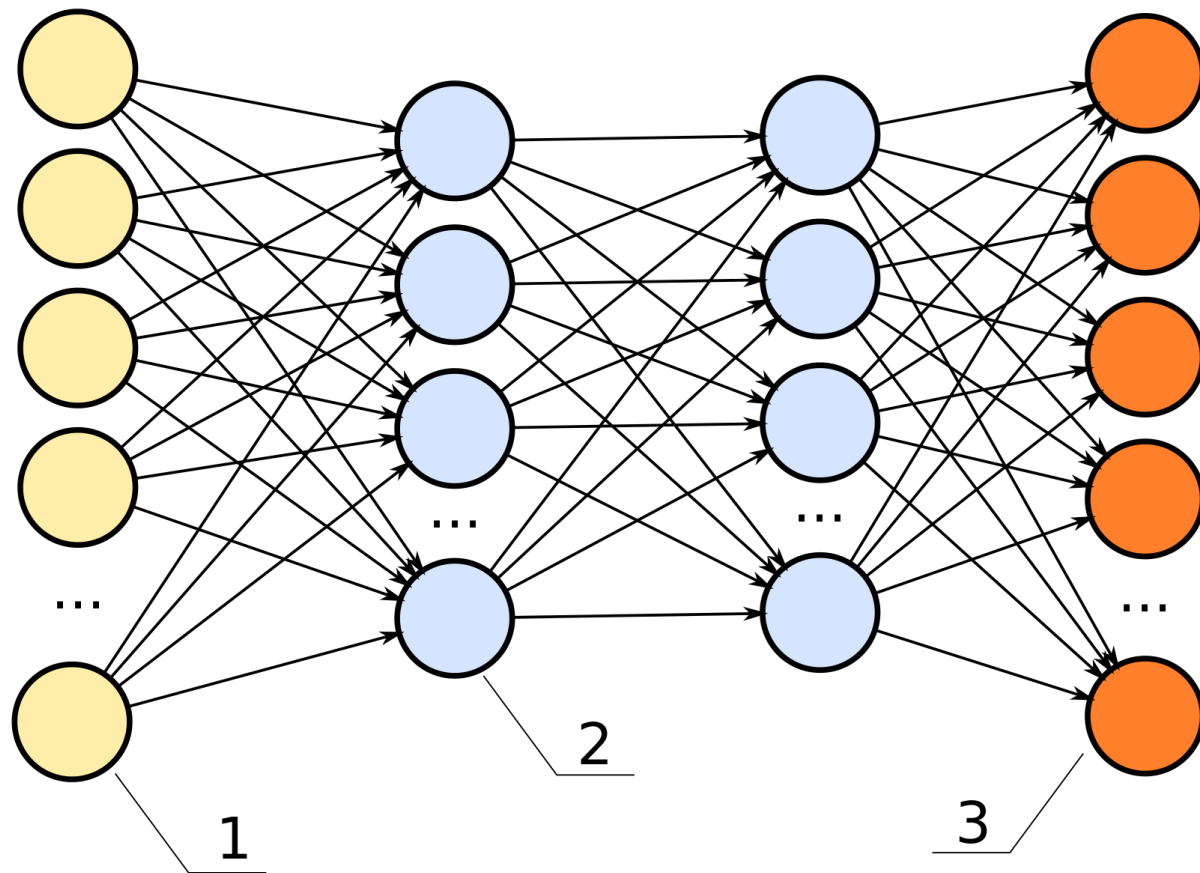
A screenshot of a window titled "Incanter Dataset" displaying a table of data. The table has five columns: "Sepal.Length", "Sepal.Width", "Petal.Length", "Petal.Width", and "Species". The data consists of 20 rows, all of which are "setosa" species. The values for the other four columns vary across the rows.

Sepal.Length	Sepal.Width	Petal.Length	Petal.Width	Species
5.1	3.5	1.4	0.2	setosa
4.9	3.0	1.4	0.2	setosa
4.7	3.2	1.3	0.2	setosa
4.6	3.1	1.5	0.2	setosa
5.0	3.6	1.4	0.2	setosa
5.4	3.9	1.7	0.4	setosa
4.6	3.4	1.4	0.3	setosa
5.0	3.4	1.5	0.2	setosa
4.4	2.9	1.4	0.2	setosa
4.9	3.1	1.5	0.1	setosa
5.4	3.7	1.5	0.2	setosa
4.8	3.4	1.6	0.2	setosa
4.8	3.0	1.4	0.1	setosa
4.3	3.0	1.1	0.1	setosa
5.8	4.0	1.2	0.2	setosa
5.7	4.4	1.5	0.4	setosa
5.4	3.9	1.3	0.4	setosa
5.1	3.5	1.4	0.3	setosa
5.7	3.8	1.7	0.3	setosa
5.1	3.8	1.5	0.3	setosa
5.4	3.4	1.7	0.2	setosa
5.1	3.7	1.5	0.4	setosa

# ANN vs other classifiers



# Fully connected neural networks



```
import torch
```

```
input_layer = torch.rand(10)
```

```
w1 = torch.rand(10, 20)
```

```
w2 = torch.rand(20, 20)
```

```
w3 = torch.rand(20, 4)
```

```
h1 = torch.matmul(input_layer, w1)
```

```
h2 = torch.matmul(h1, w2)
```

```
output_layer = torch.matmul(h2, w3)
```

```
print(output_layer)
```

```
tensor([413.8647, 286.5770,  
        361.8974, 294.0240])
```

# Building a neural network - PyTorch style

```
import torch
import torch.nn as nn

class Net(nn.Module):
    def __init__(self):
        super(Net, self).__init__()
        self.fc1 = nn.Linear(10, 20)
        self.fc2 = nn.Linear(20, 20)
        self.output = nn.Linear(20, 4)

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

```
input_layer = torch.rand(10)
net = Net()
result = net(input_layer)
```

# Let's practice!

INTRODUCTION TO DEEP LEARNING WITH PYTORCH