

Introduction to deep learning with PyTorch

INTRODUCTION TO DEEP LEARNING WITH PYTORCH

Jasmin Ludolf

Senior Data Science Content Developer,
DataCamp



Deep learning is everywhere!



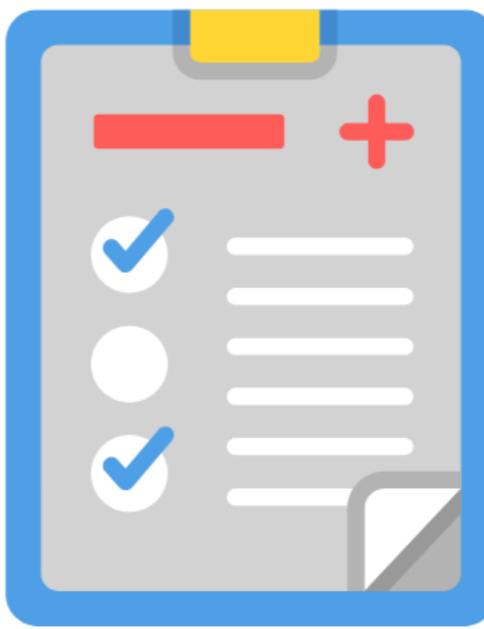
Deep learning is everywhere!



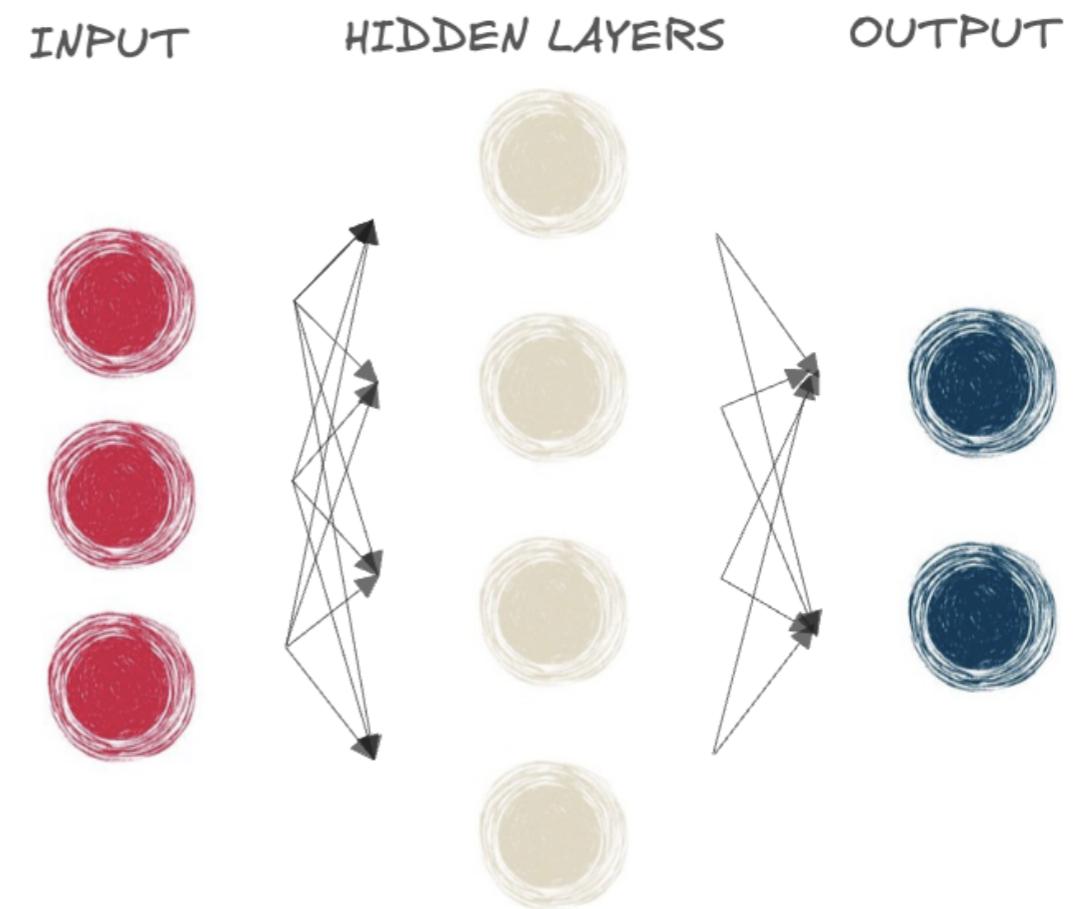
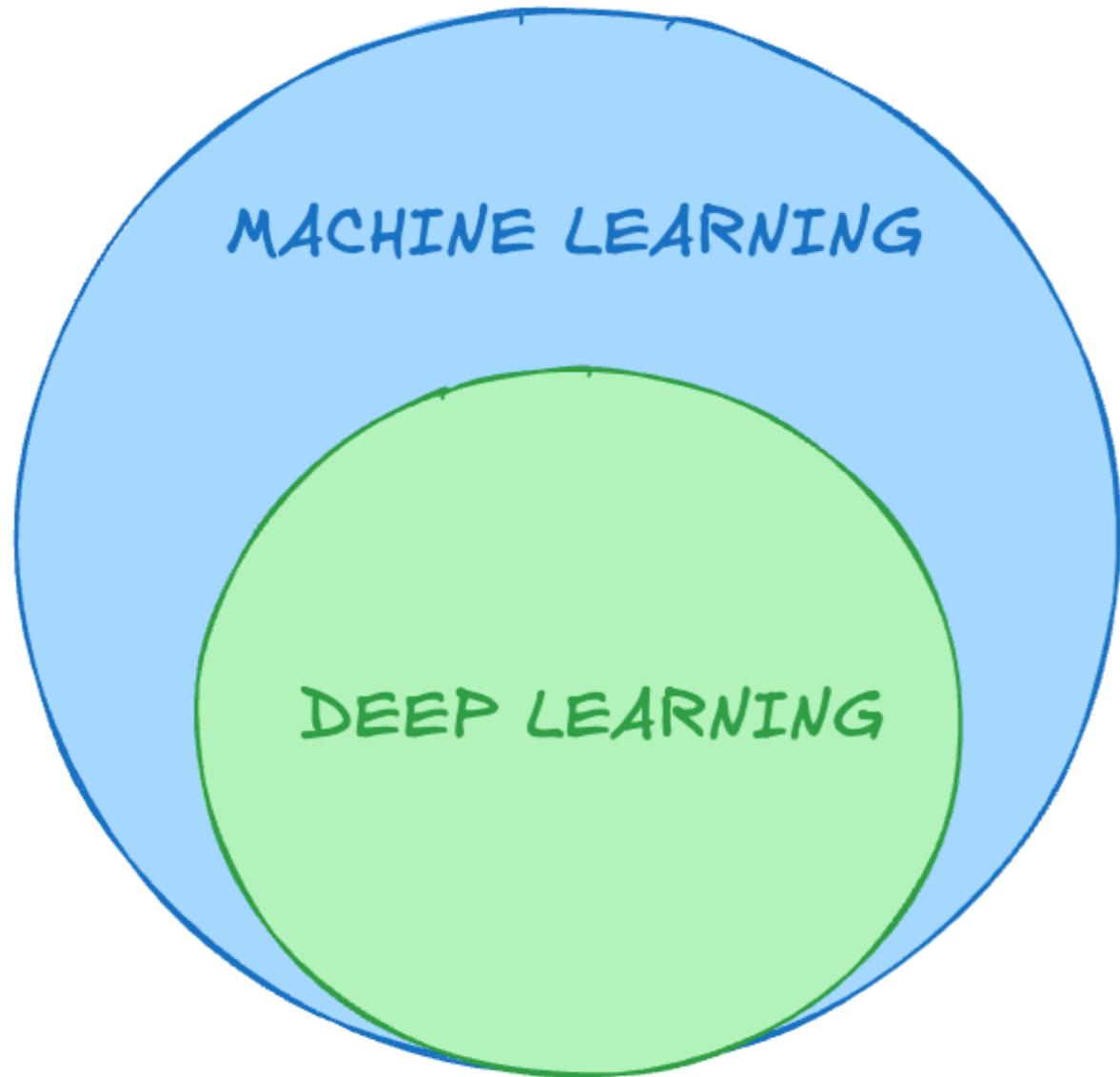
Deep learning is everywhere!



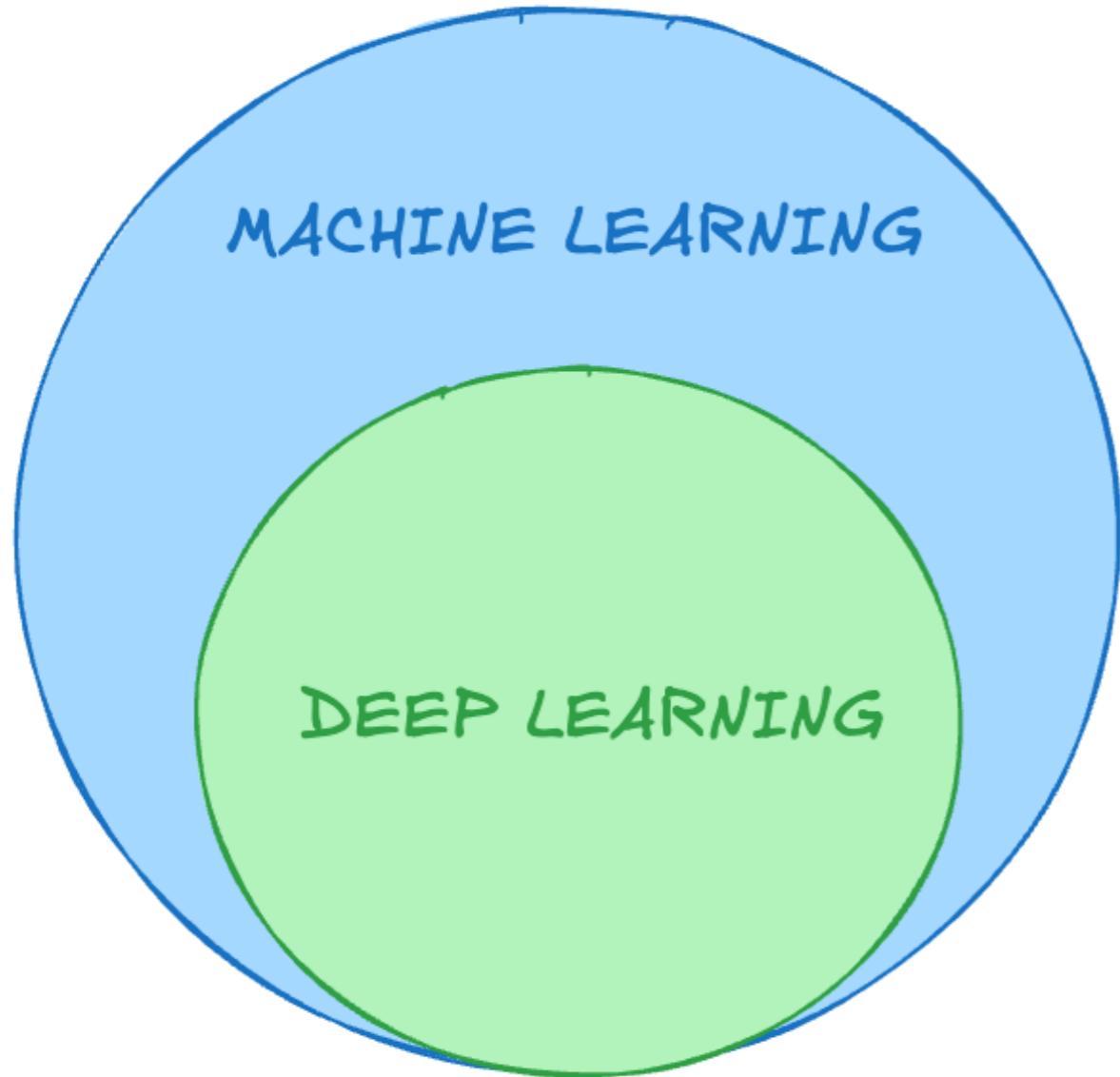
Deep learning is everywhere!



What is deep learning?



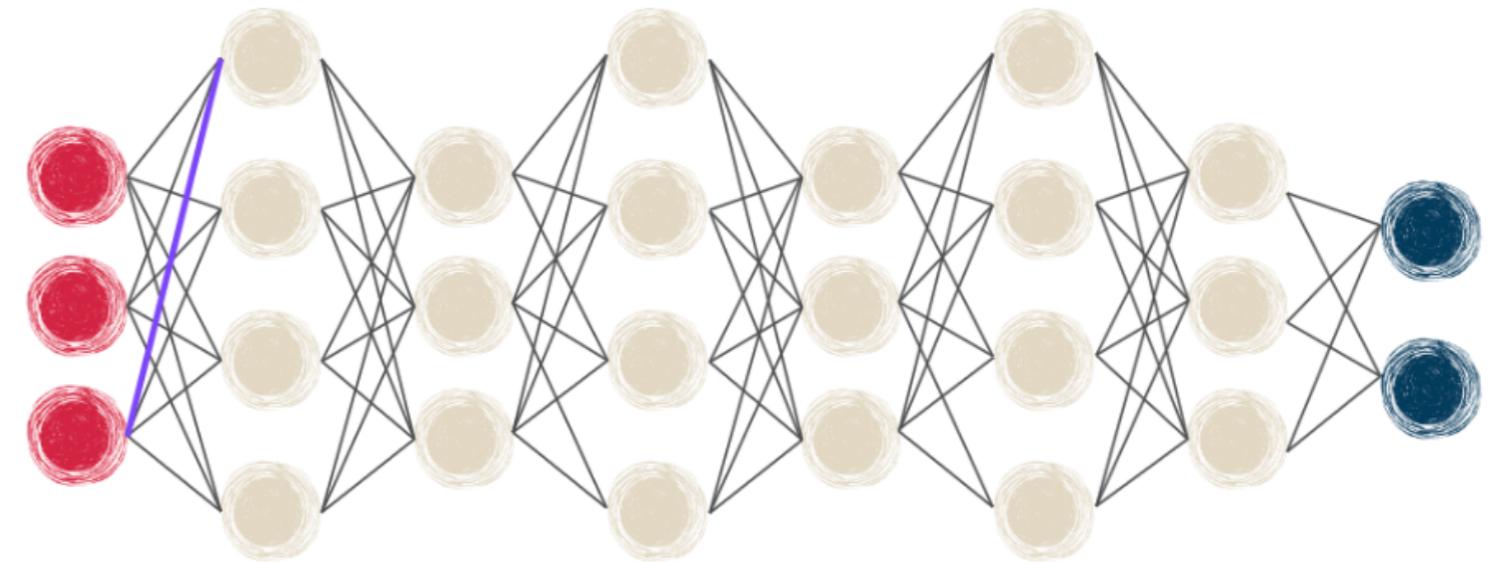
What is deep learning?



INPUT

HIDDEN LAYERS

OUTPUT



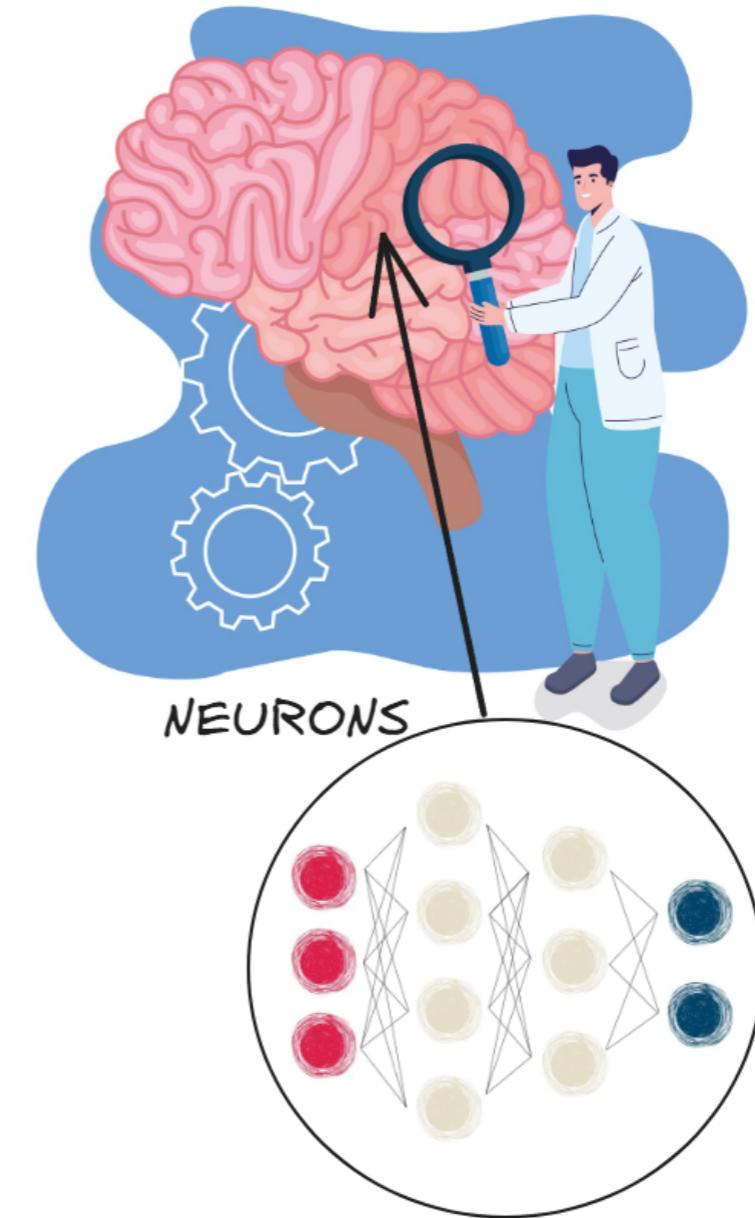
Deep learning networks

- Inspired by how the human brain learns



Deep learning networks

- Inspired by how the human brain learns
- Neurons → neural networks
- Models require large amount of data
- At least 100,000s data points



PyTorch: a deep learning framework

- One of the most popular frameworks
- Originally developed by Meta AI, now part of Linux Foundation
- Intuitive and user-friendly
- Similarities with NumPy



PyTorch tensors

- Tensor:
 - Similar to array or matrix
 - Building block of neural networks

```
import torch  
my_list = [[1, 2, 3], [4, 5, 6]]  
tensor = torch.tensor(my_list)  
print(tensor)
```

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

Tensor attributes

- Tensor shape

```
my_list = [[1, 2, 3], [4, 5, 6]]  
tensor = torch.tensor(my_list)  
print(tensor.shape)
```

```
torch.Size([2, 3])
```

- Tensor data type

```
print(tensor.dtype)
```

```
torch.int64
```

Getting started with tensor operations

Compatible shapes

```
a = torch.tensor([[1, 1],  
                 [2, 2]])
```

```
b = torch.tensor([[2, 2],  
                 [3, 3]])
```

- Addition / subtraction

```
print(a + b)
```

```
tensor([[3, 3],  
       [5, 5]])
```

Incompatible shapes

```
a = torch.tensor([[1, 1],  
                 [2, 2]])
```

```
c = torch.tensor([[2, 2, 4],  
                 [3, 3, 5]])
```

- Addition / subtraction

```
print(a + c)
```

```
RuntimeError: The size of tensor a  
(2) must match the size of tensor b (3)  
at non-singleton dimension 1
```

Element-wise multiplication

```
a = torch.tensor([[1, 1],  
                  [2, 2]])  
  
b = torch.tensor([[2, 2],  
                  [3, 3]])  
  
print(a * b)
```

```
tensor([[2, 2],  
       [6, 6]])
```

Matrix multiplication

```
a = torch.tensor([[1, 1],  
                  [2, 2]])  
  
b = torch.tensor([[2, 2],  
                  [3, 3]])  
  
print(a @ b)
```

```
tensor([[5, 5],  
        [10, 10]])
```

Matrix multiplication

```
a = torch.tensor([[1, 1],  
                  [2, 2]])  
  
b = torch.tensor([[2, 2],  
                  [3, 3]])  
  
print(a @ b)
```

```
tensor([[5, 5],  
        [10, 10]])
```

- $1 \cdot 2 + 1 \cdot 3 = 5$
- Perform addition and multiplication to process data and learn patterns

Let's practice!

INTRODUCTION TO DEEP LEARNING WITH PYTORCH

Neural networks and layers

INTRODUCTION TO DEEP LEARNING WITH PYTORCH

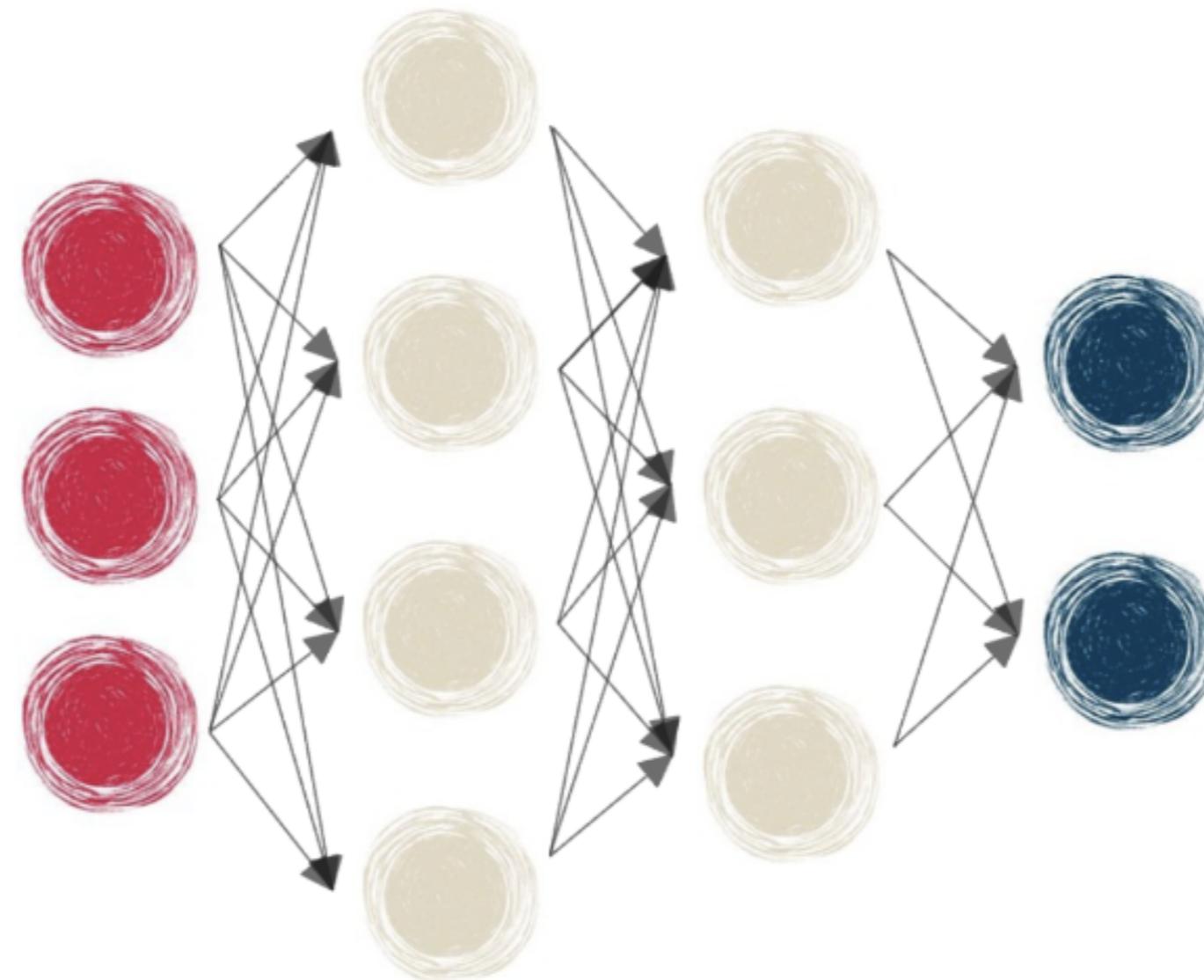


Jasmin Ludolf

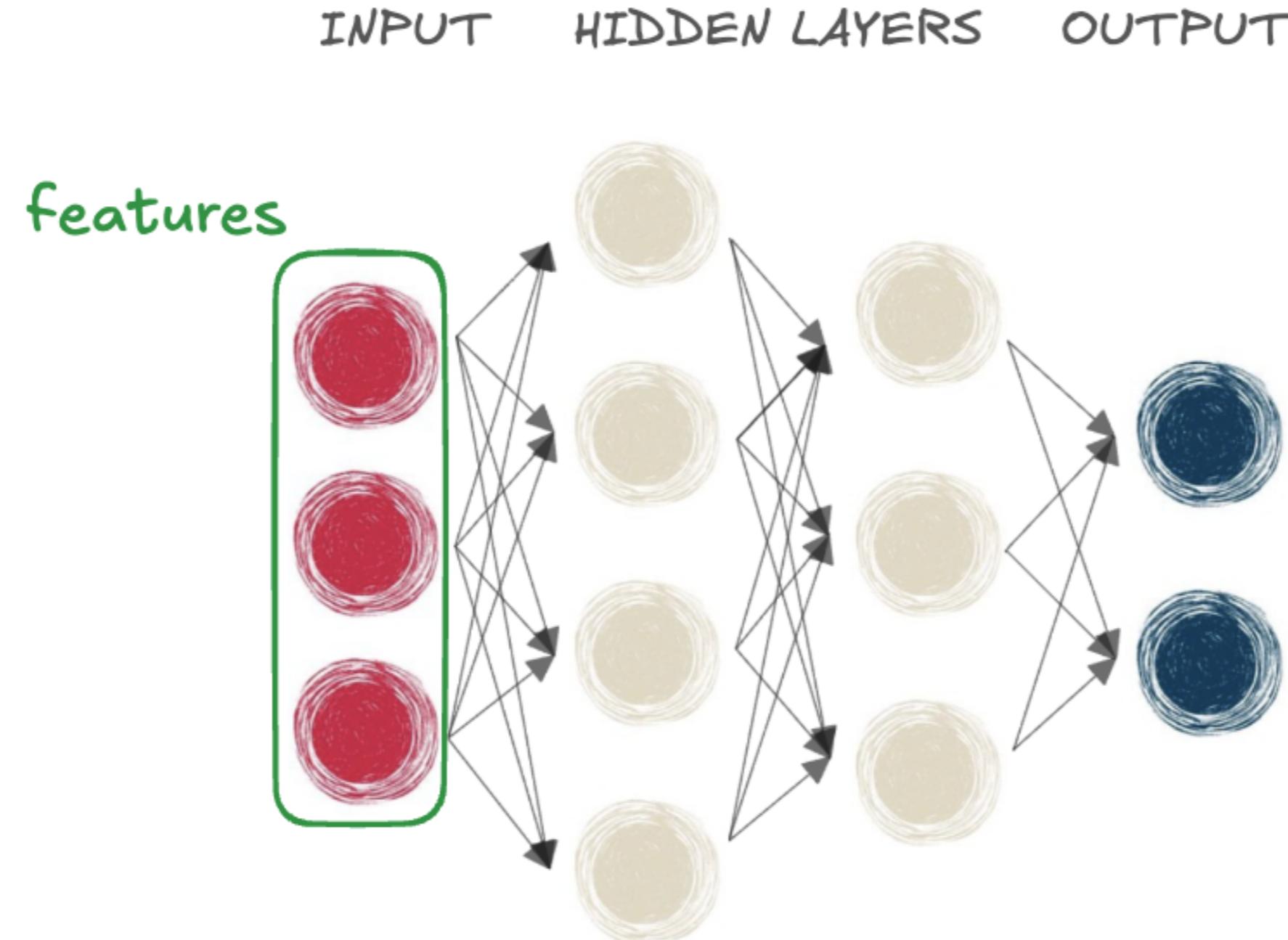
Senior Data Science Content Developer,
DataCamp

Neural network layers

INPUT HIDDEN LAYERS OUTPUT

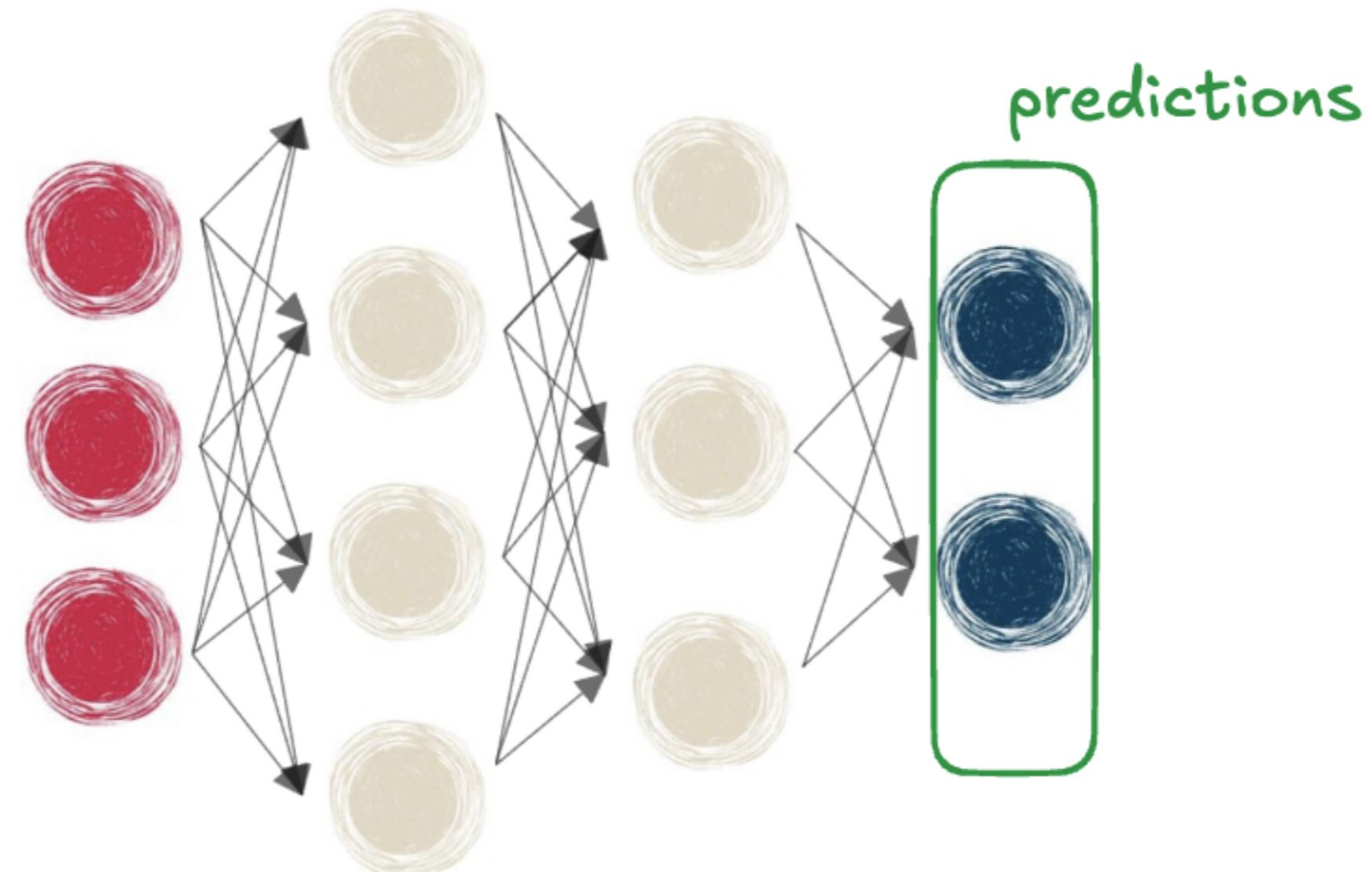


Neural network layers



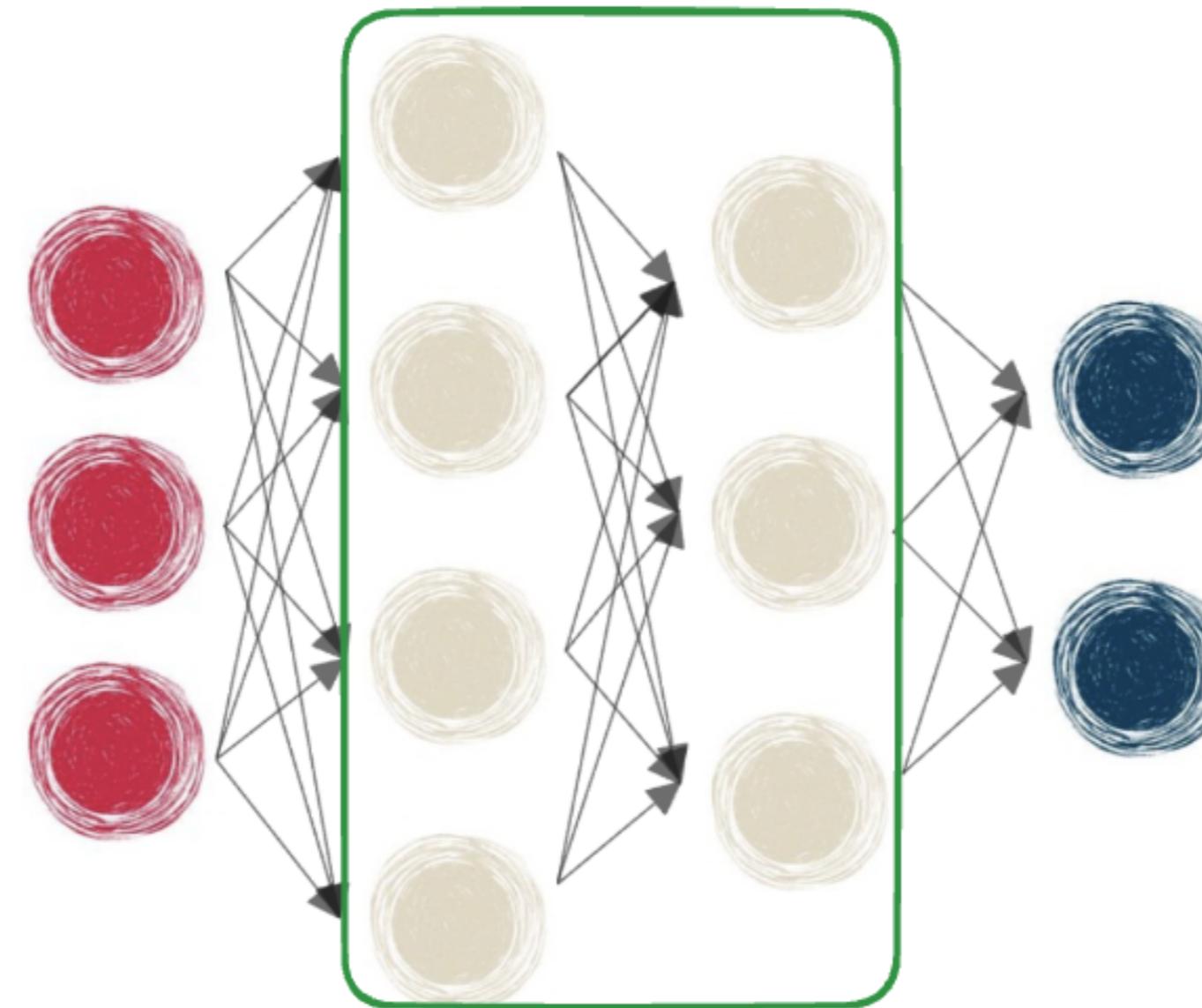
Neural network layers

INPUT HIDDEN LAYERS OUTPUT

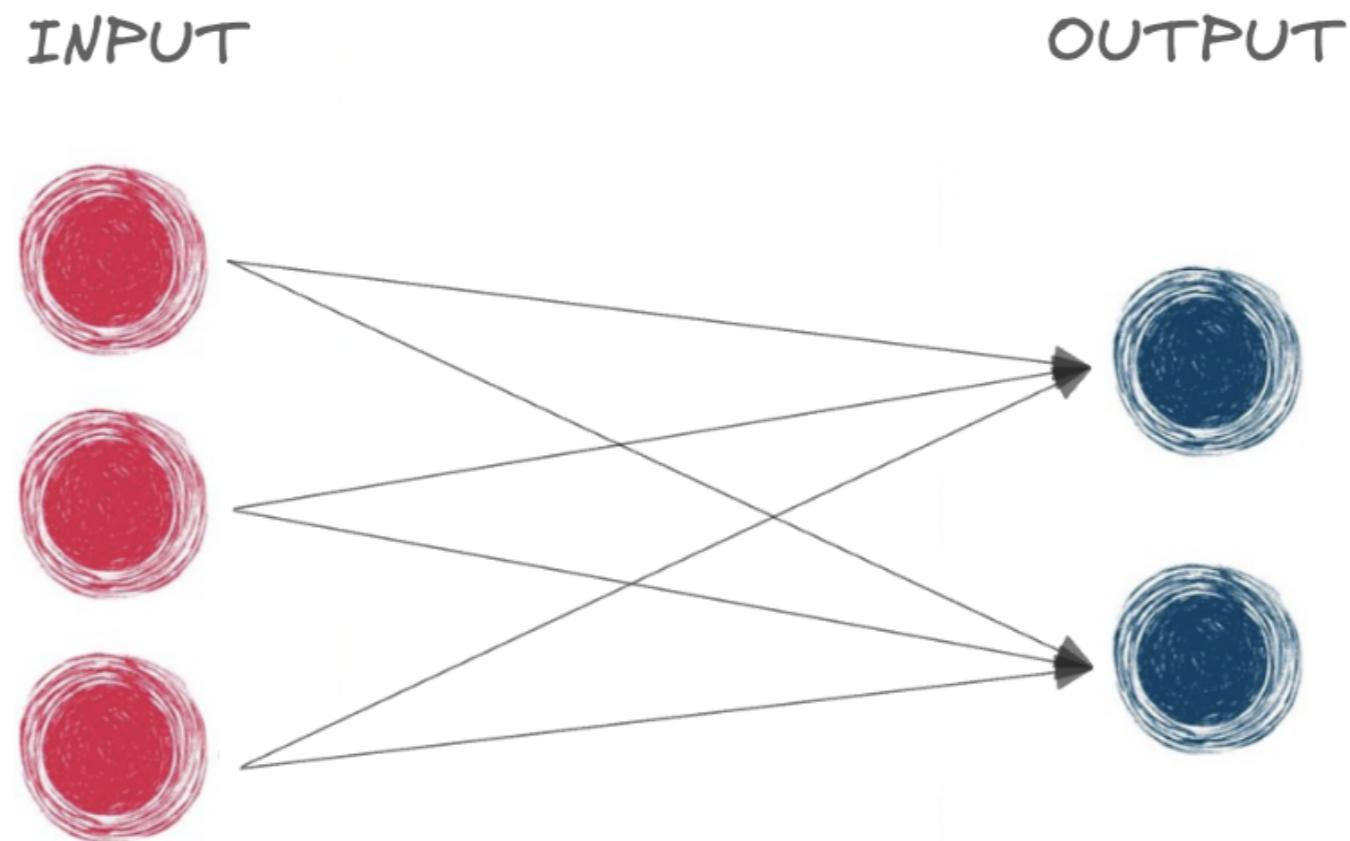


Neural network layers

INPUT HIDDEN LAYERS OUTPUT



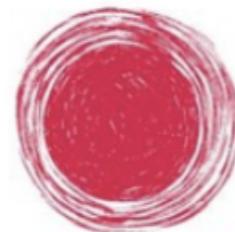
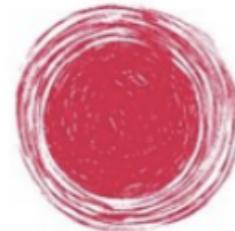
Our first neural network



- Fully connected network
- Equivalent to a linear model

Designing a neural network

INPUT

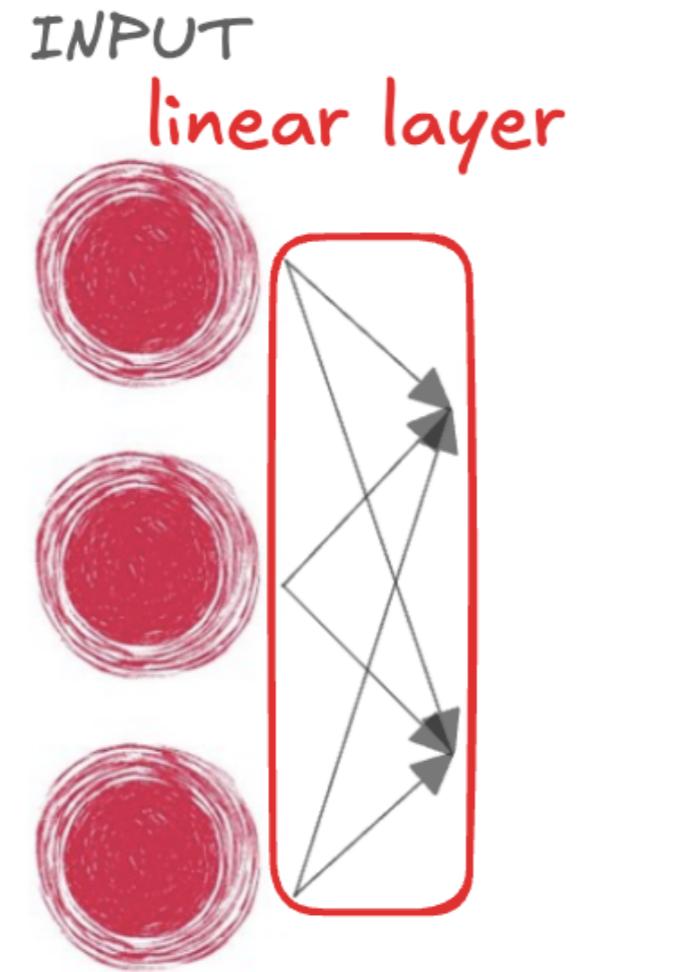


```
# Importing as nn to avoid writing torch.nn  
import torch.nn as nn
```

```
# Create input_tensor with three features  
input_tensor = torch.tensor(  
    [[0.3471, 0.4547, -0.2356]])
```

- Input neurons = features
- Output neurons = classes

Designing a neural network

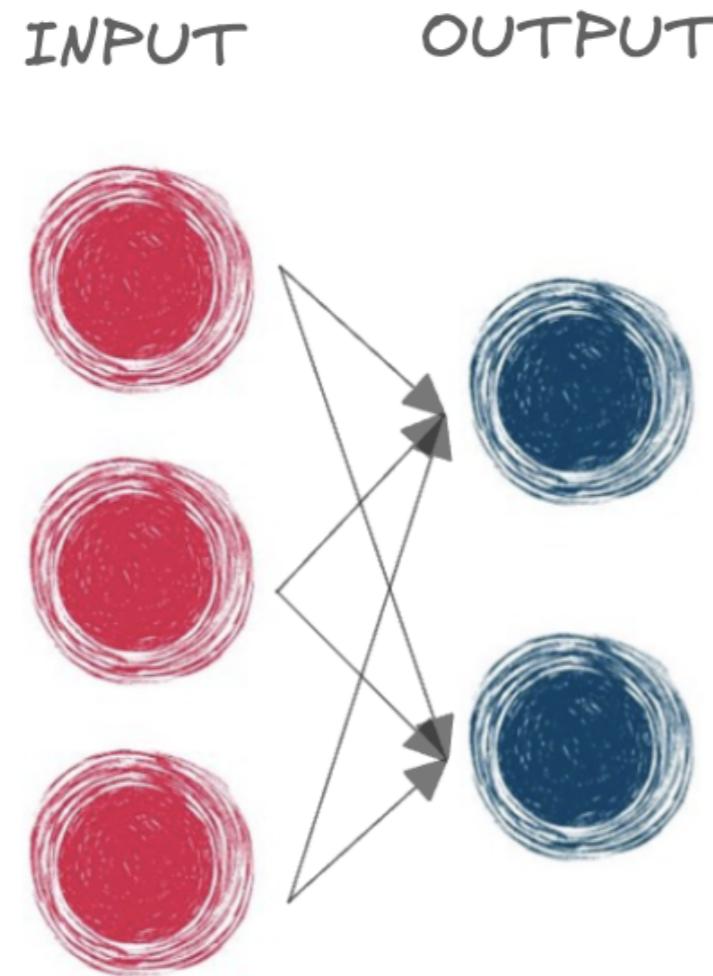


```
# Importing as nn to avoid writing torch.nn
import torch.nn as nn

# Create input_tensor with three features
input_tensor = torch.tensor(
    [[0.3471, 0.4547, -0.2356]])

# Define our linear layer
linear_layer = nn.Linear(
    in_features=3,
    out_features=2
)
```

Designing a neural network



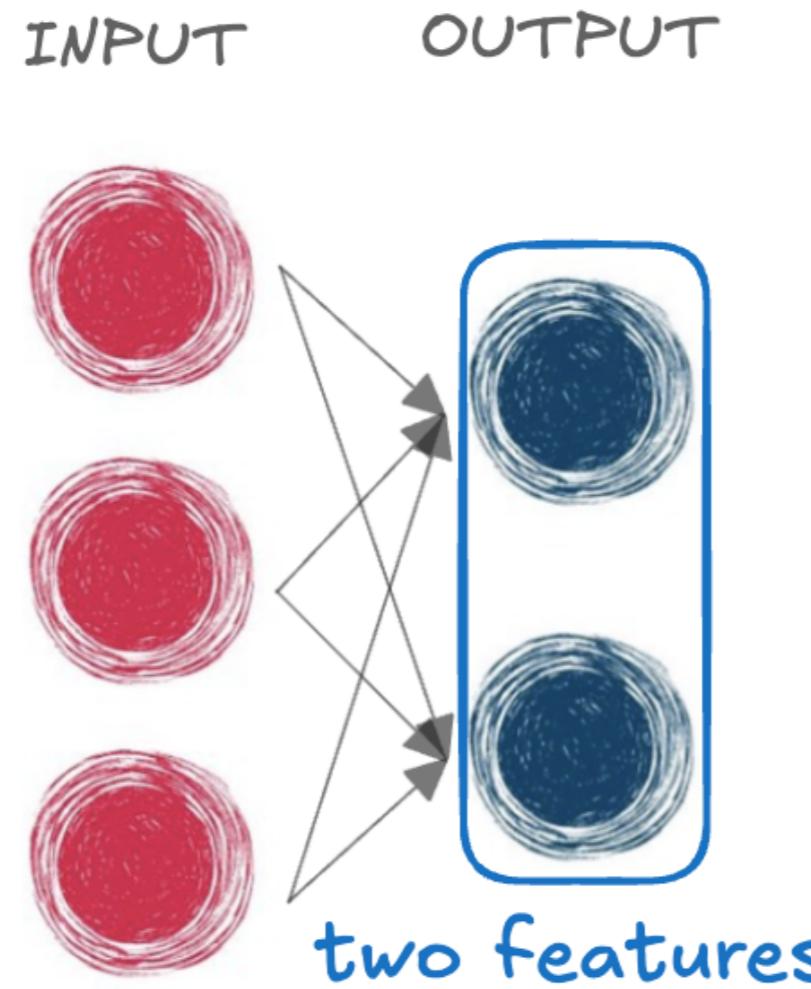
```
# Importing as nn to avoid writing torch.nn
import torch.nn as nn

# Create input_tensor with three features
input_tensor = torch.tensor(
    [[0.3471, 0.4547, -0.2356]])

# Define our linear layer
linear_layer = nn.Linear(
    in_features=3,
    out_features=2
)

# Pass input through linear layer
output = linear_layer(input_tensor)
print(output)
```

Designing a neural network

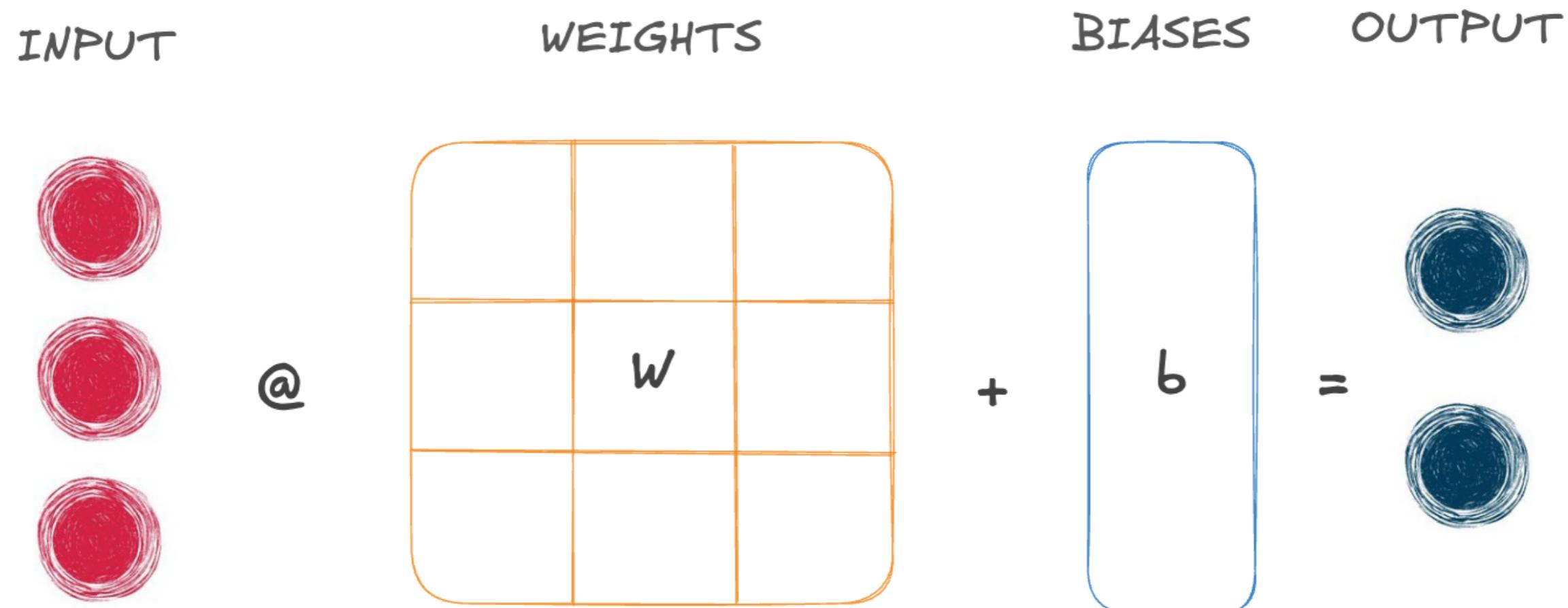


```
# Pass input through linear layer  
output = linear_layer(input_tensor)  
print(output)
```

```
tensor([[-0.2415, -0.1604]],  
grad_fn=<AddmmBackward0>)
```

Weights and biases

```
output = linear_layer(input_tensor)
```



Weights and biases

- `.weight`

```
print(linear_layer.weight)
```

Parameter containing:

```
tensor([[-0.4799,  0.4996,  0.1123],  
       [-0.0365, -0.1855,  0.0432]],  
      requires_grad=True)
```

- `.bias`

```
print(linear_layer.bias)
```

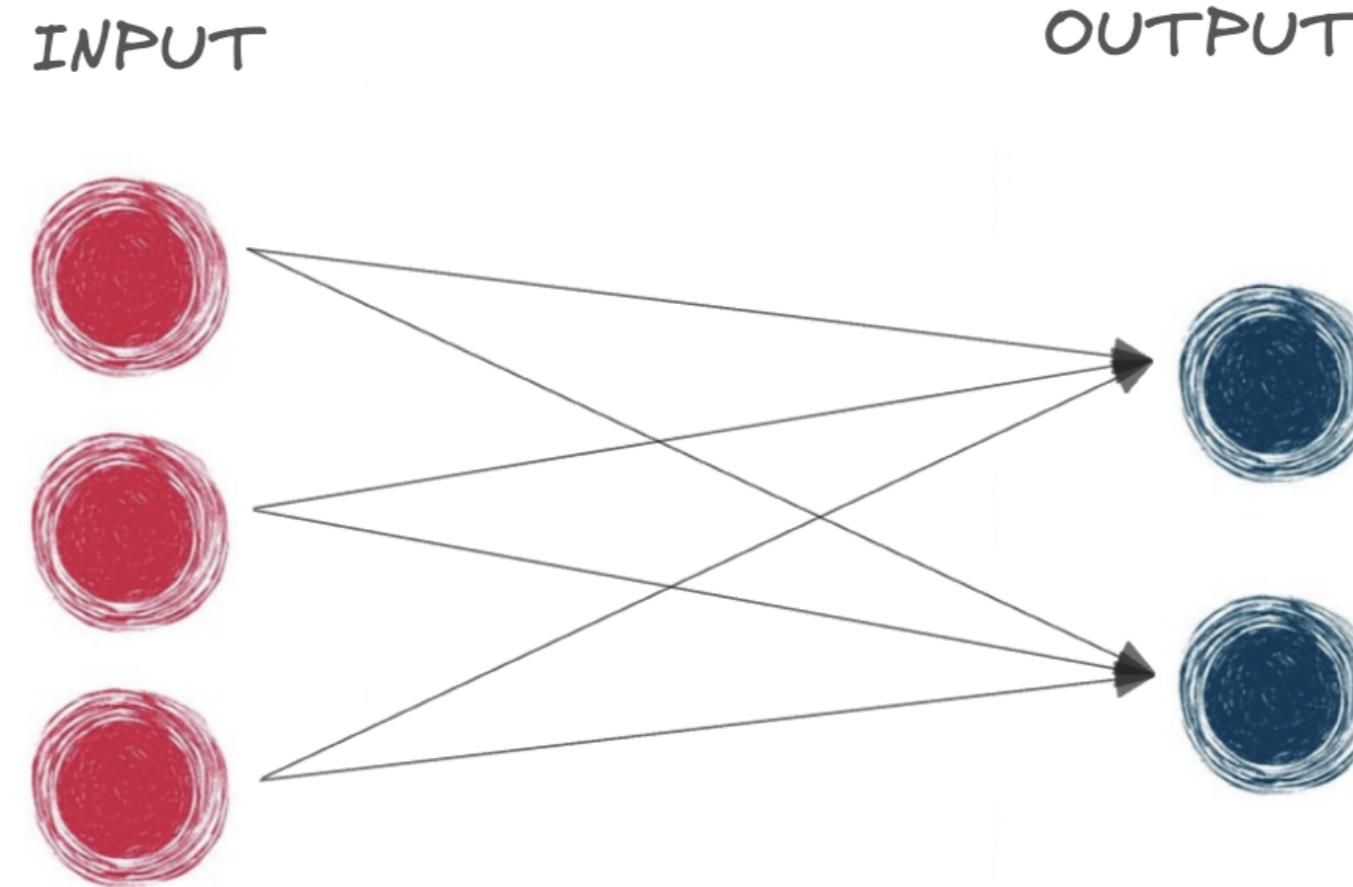
Parameter containing:

```
tensor([0.0310, 0.1537], requires_grad=True)
```

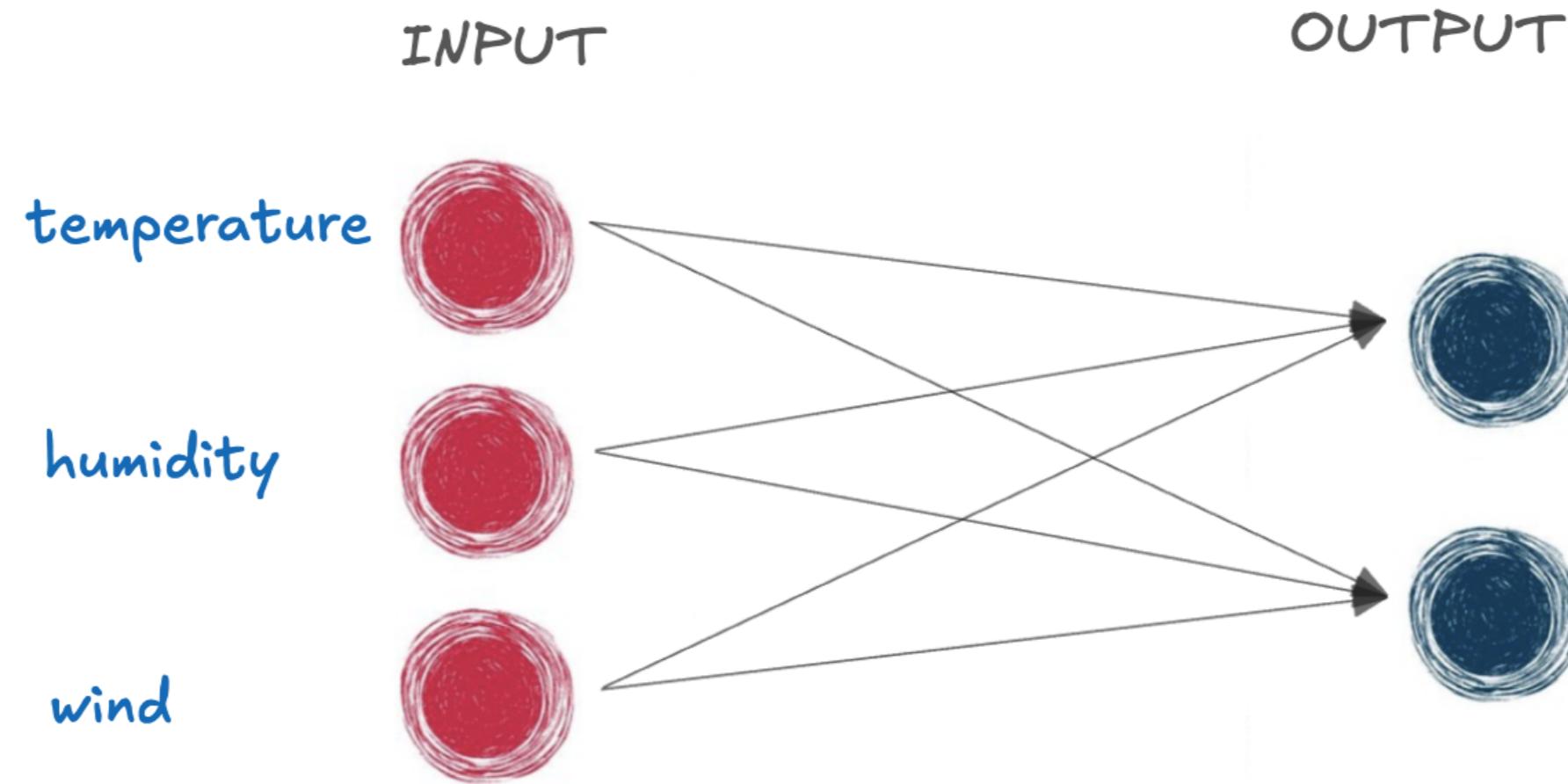
- Reflects the importance of different features

- Provides the neuron with a baseline output

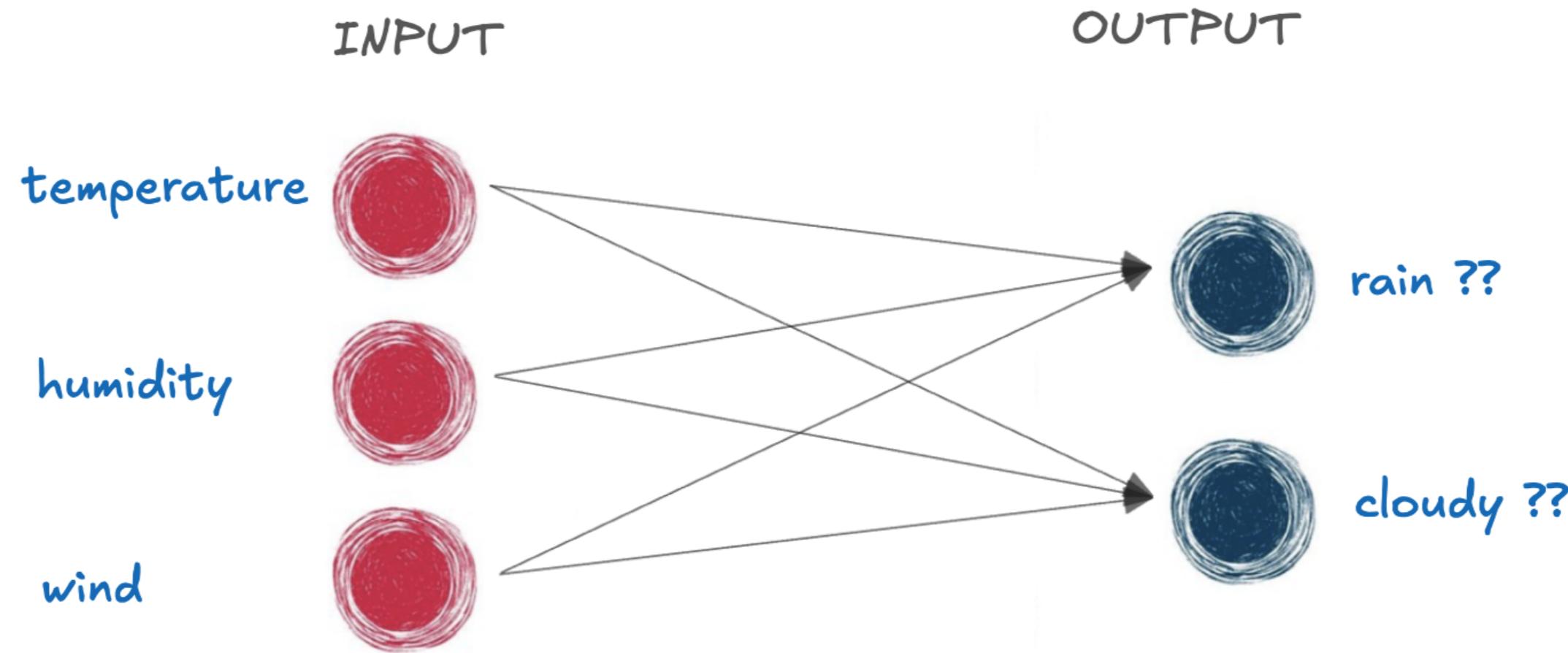
A fully connected network in action



A fully connected network in action



A fully connected network in action



- Humidity feature will have a more significant **weight**
- Bias is to account for baseline information

Let's practice!

INTRODUCTION TO DEEP LEARNING WITH PYTORCH

Hidden layers and parameters

INTRODUCTION TO DEEP LEARNING WITH PYTORCH

Jasmin Ludolf

Senior Data Science Content Developer,
DataCamp



Stacking layers with nn.Sequential()

```
# Create network with three linear layers
model = nn.Sequential(
    nn.Linear(n_features, 8),
    nn.Linear(8, 4),
    nn.Linear(4, n_classes)
)
```

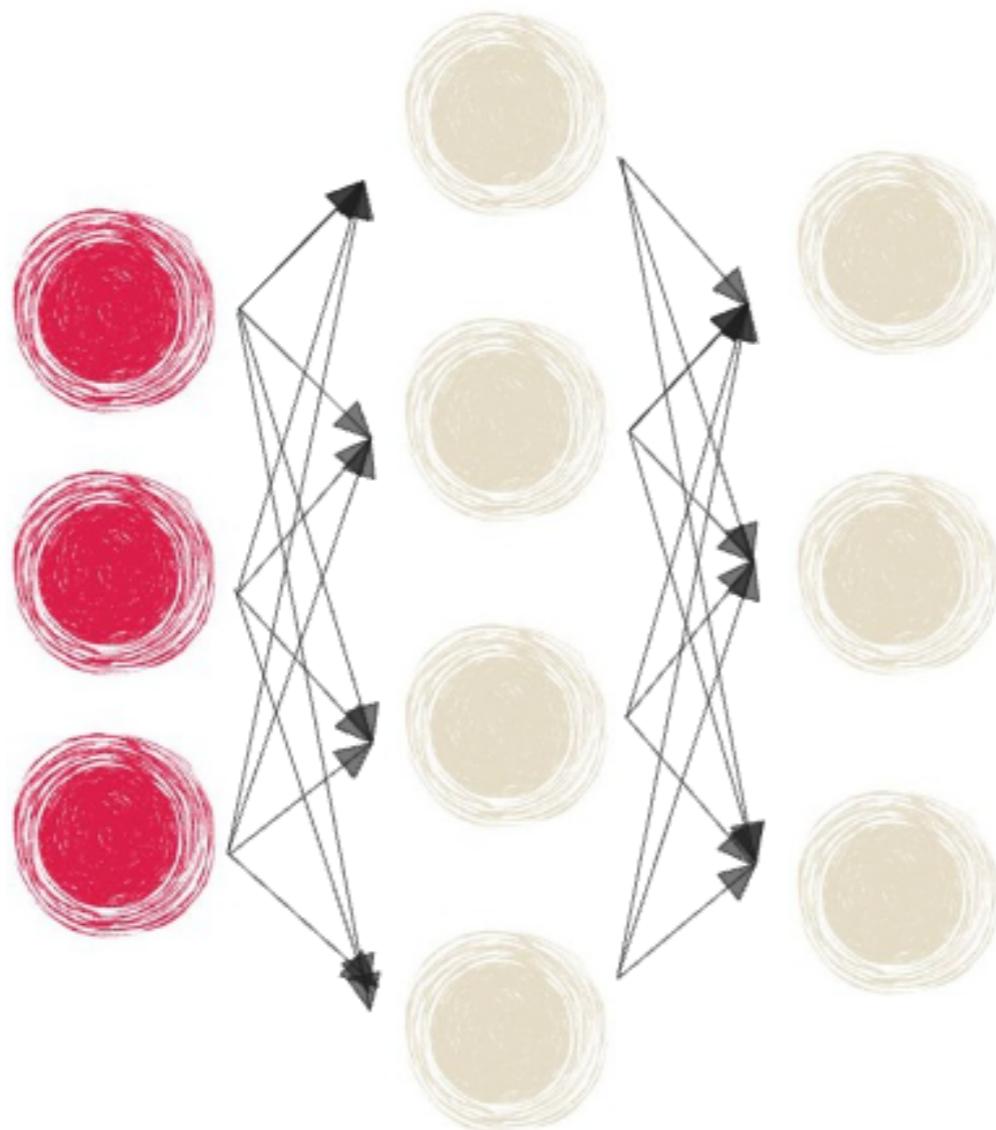
- Input is passed through the linear layers
- Layers within `nn.Sequential()` are hidden layers

Stacking layers with nn.Sequential()

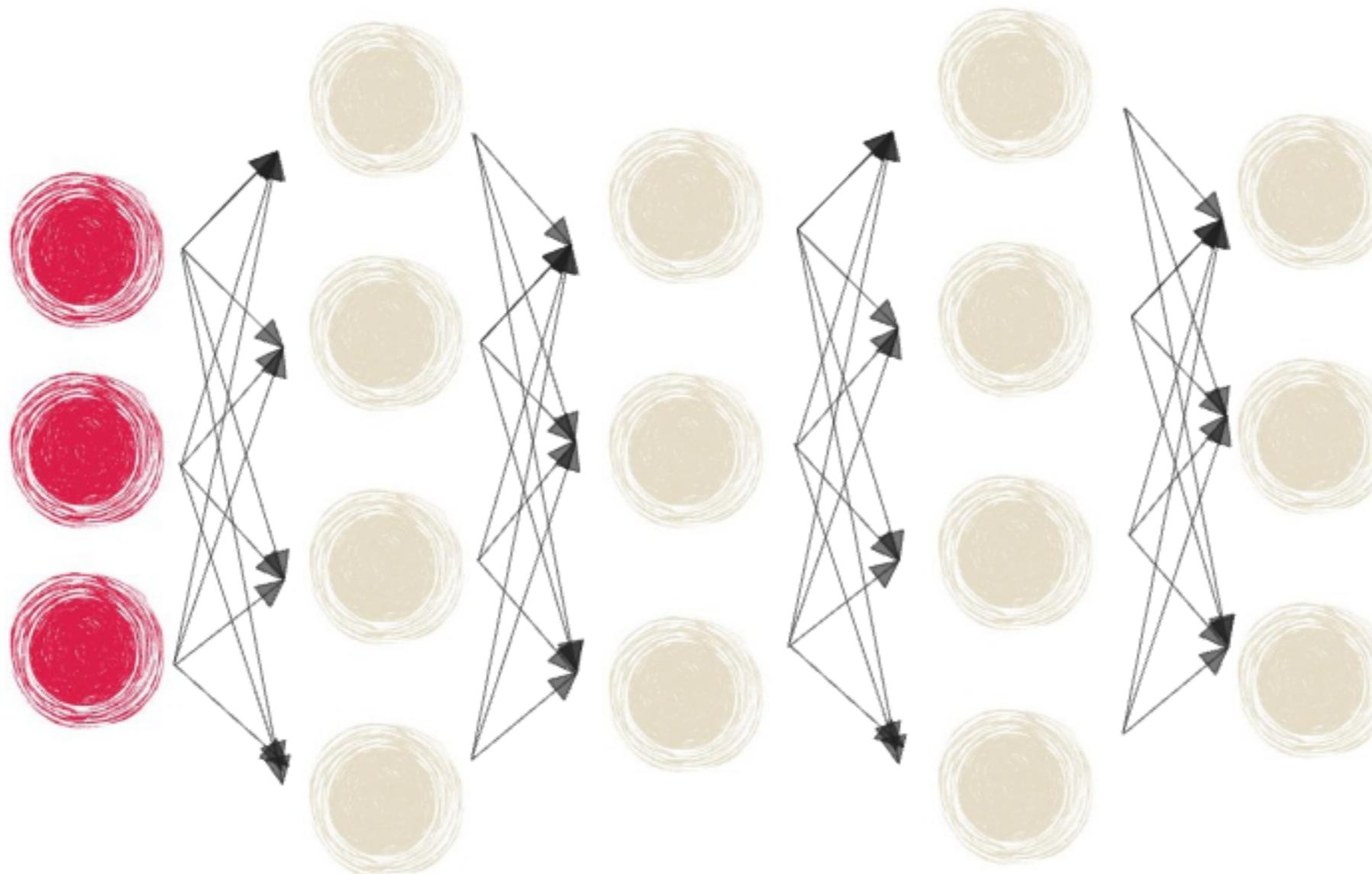
```
# Create network with three linear layers
model = nn.Sequential(
    nn.Linear(n_features, 8), # n_features represents number of input features
    nn.Linear(8, 4),
    nn.Linear(4, n_classes) # n_classes represents the number of output classes
)
```

- Input is passed through the linear layers
- Layers within `nn.Sequential()` are hidden layers
- `n_features` and `n_classes` are defined by the dataset

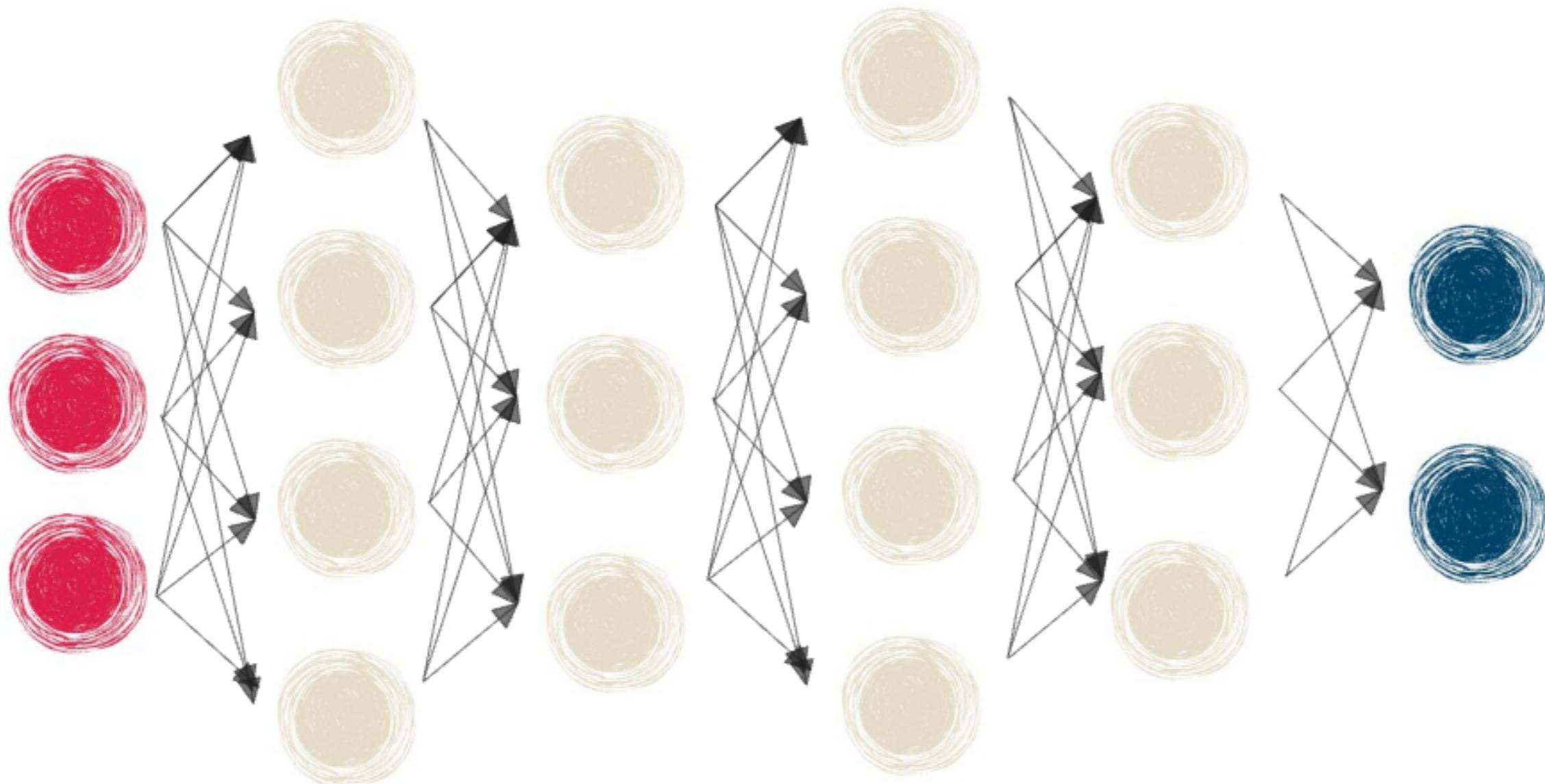
Adding layers



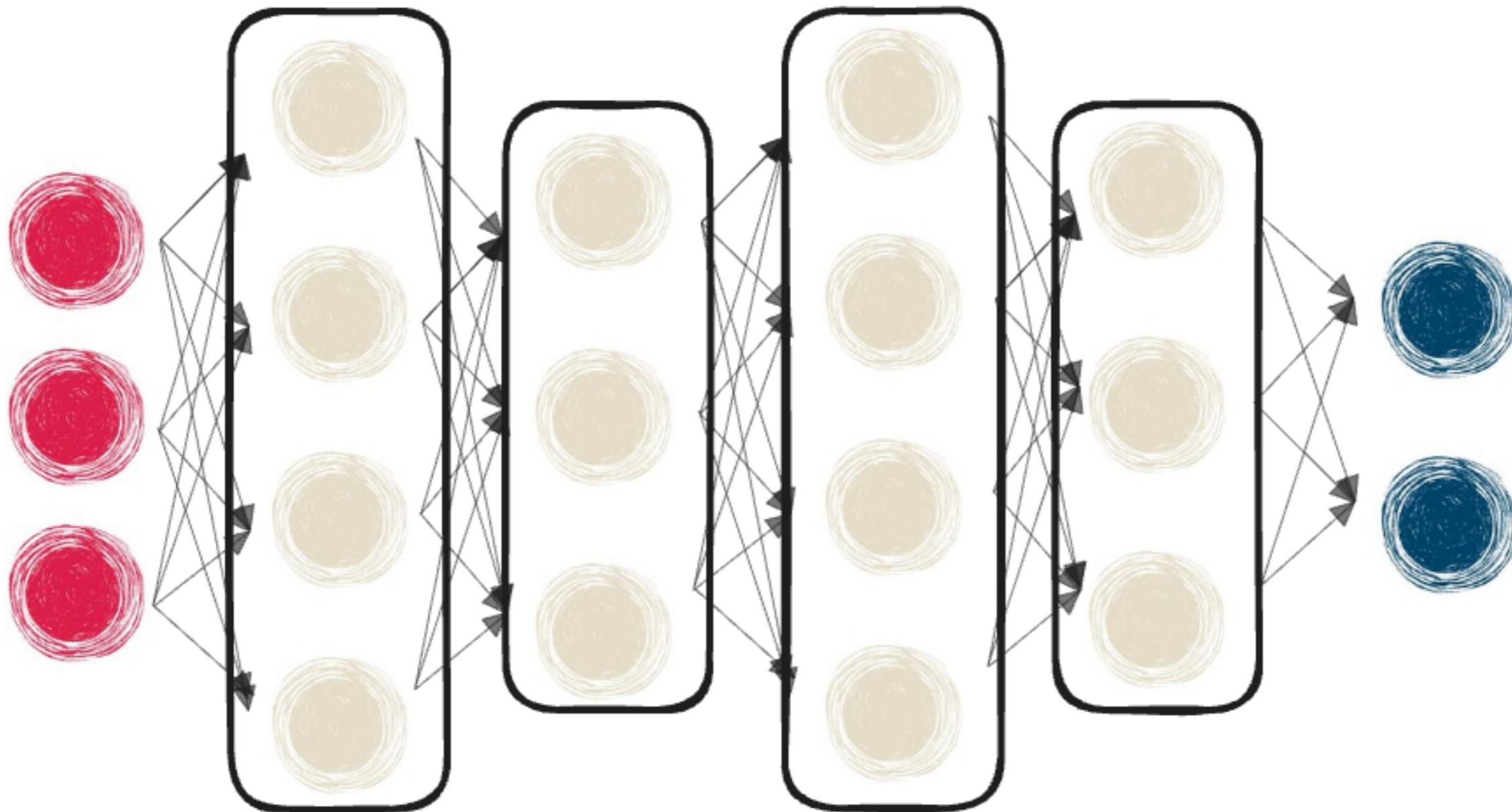
Adding layers



Adding layers



Adding layers



Adding layers

```
# Create network with three linear layers
model = nn.Sequential(
    nn.Linear(10, 18),
    nn.Linear(18, 20),
    nn.Linear(20, 5)
)
```

Adding layers

```
# Create network with three linear layers
model = nn.Sequential(
    nn.Linear(10, 18), # Takes 10 features and outputs 18
    nn.Linear(18, 20),
    nn.Linear(20, 5)
)
```

- **Input 10 → output 18 → output 20 → Output 5**

Adding layers

```
# Create network with three linear layers
model = nn.Sequential(
    nn.Linear(10, 18),
    nn.Linear(18, 20), # Takes 18 and outputs 20
    nn.Linear(20, 5)
)
```

- **Input 10 → output 18 → output 20 → Output 5**

Adding layers

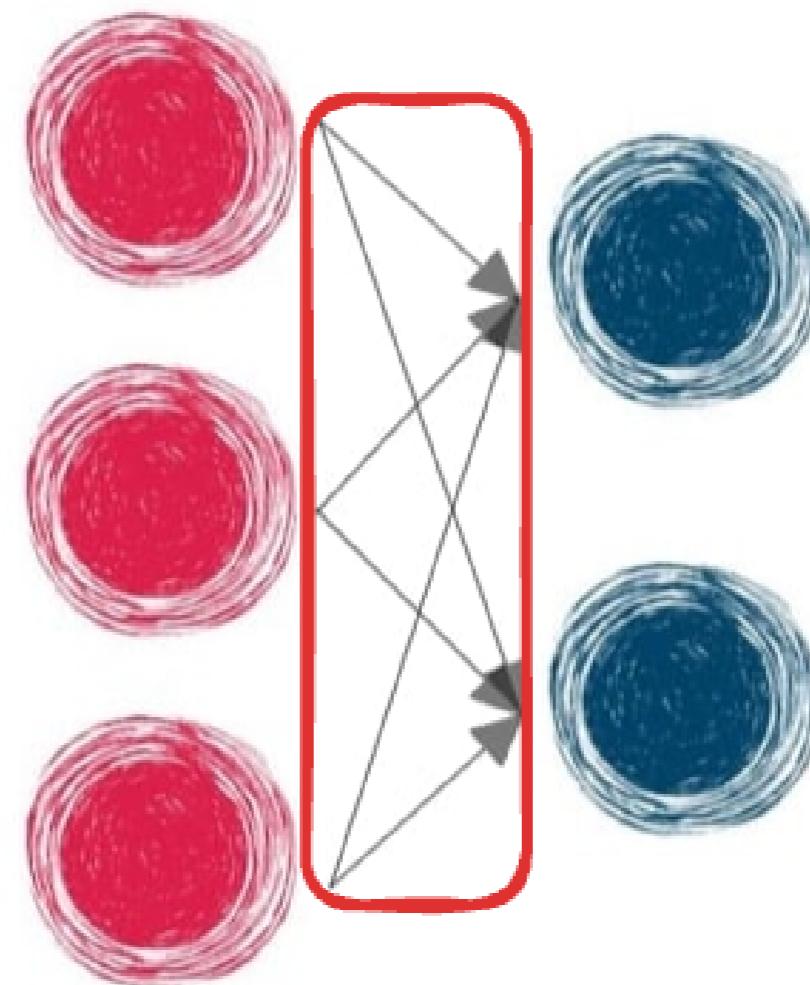
```
# Create network with three linear layers
model = nn.Sequential(
    nn.Linear(10, 18),
    nn.Linear(18, 20),
    nn.Linear(20, 5) # Takes 20 and outputs 5
)
```

- **Input 10 → output 18 → output 20 → Output 5**

Layers are made of neurons

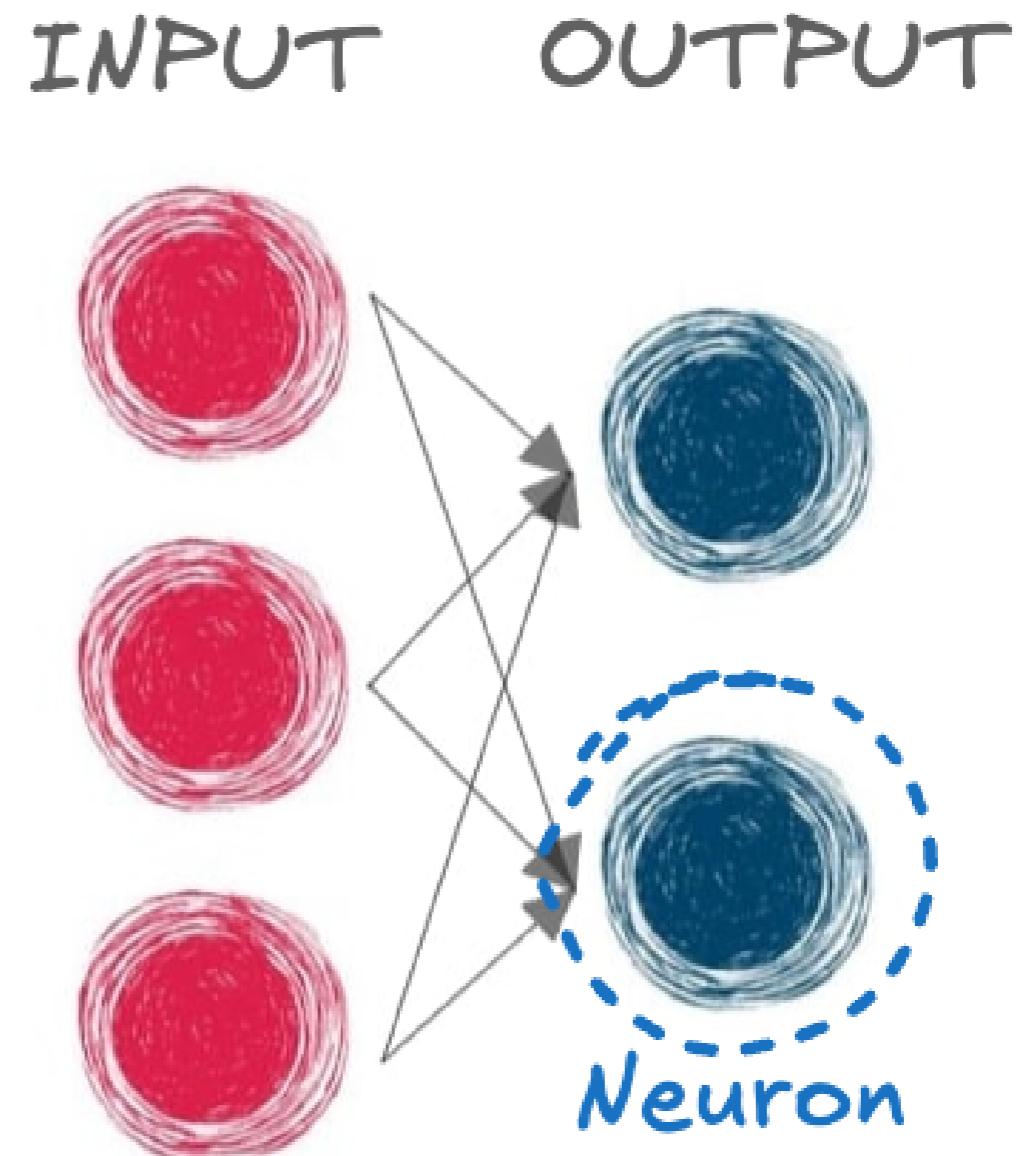
- Fully connected when each neuron links to all neurons in the previous layer

INPUT OUTPUT



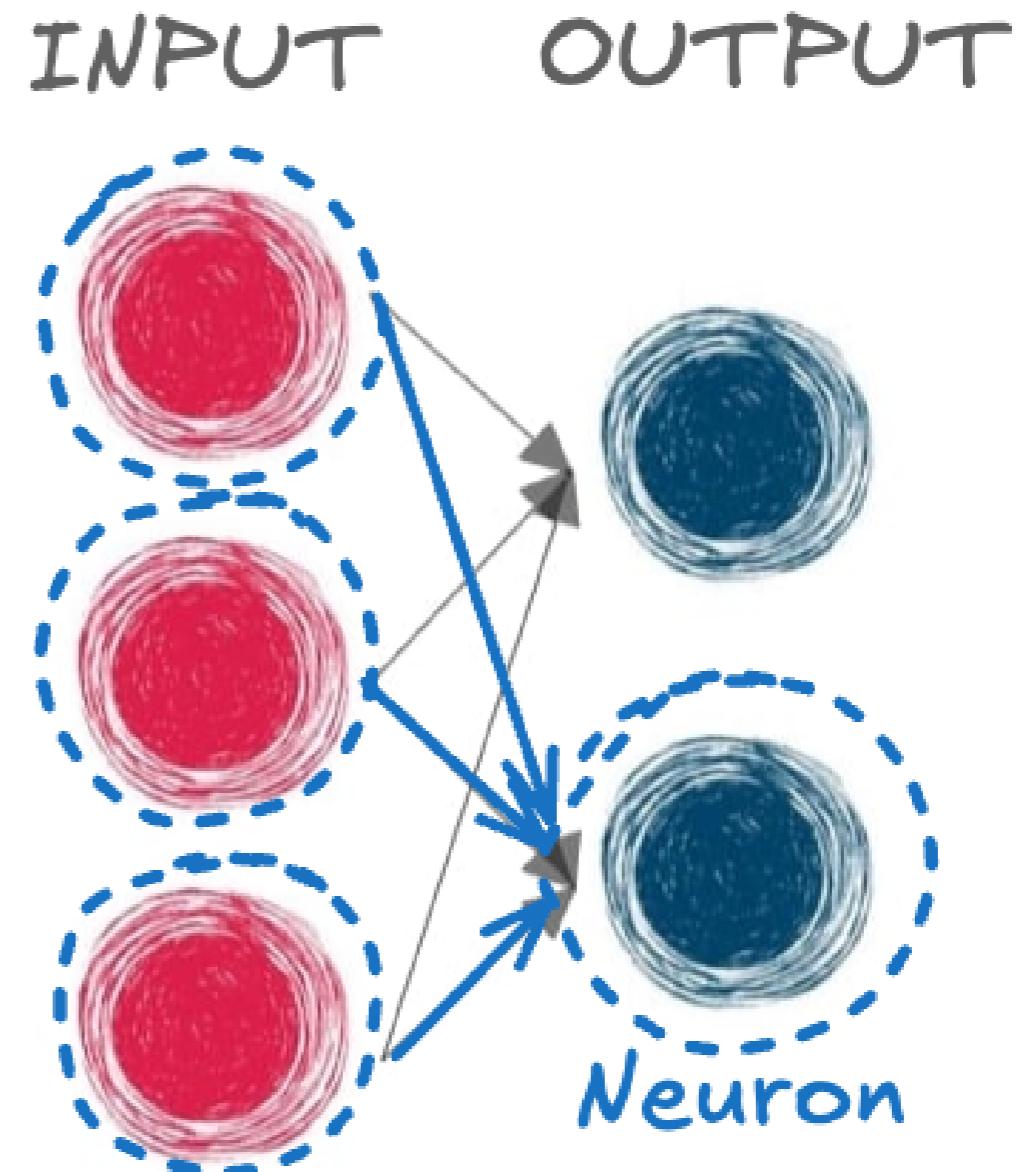
Layers are made of neurons

- Fully connected when each neuron links to all neurons in the previous layer
- A neuron in a linear layer:



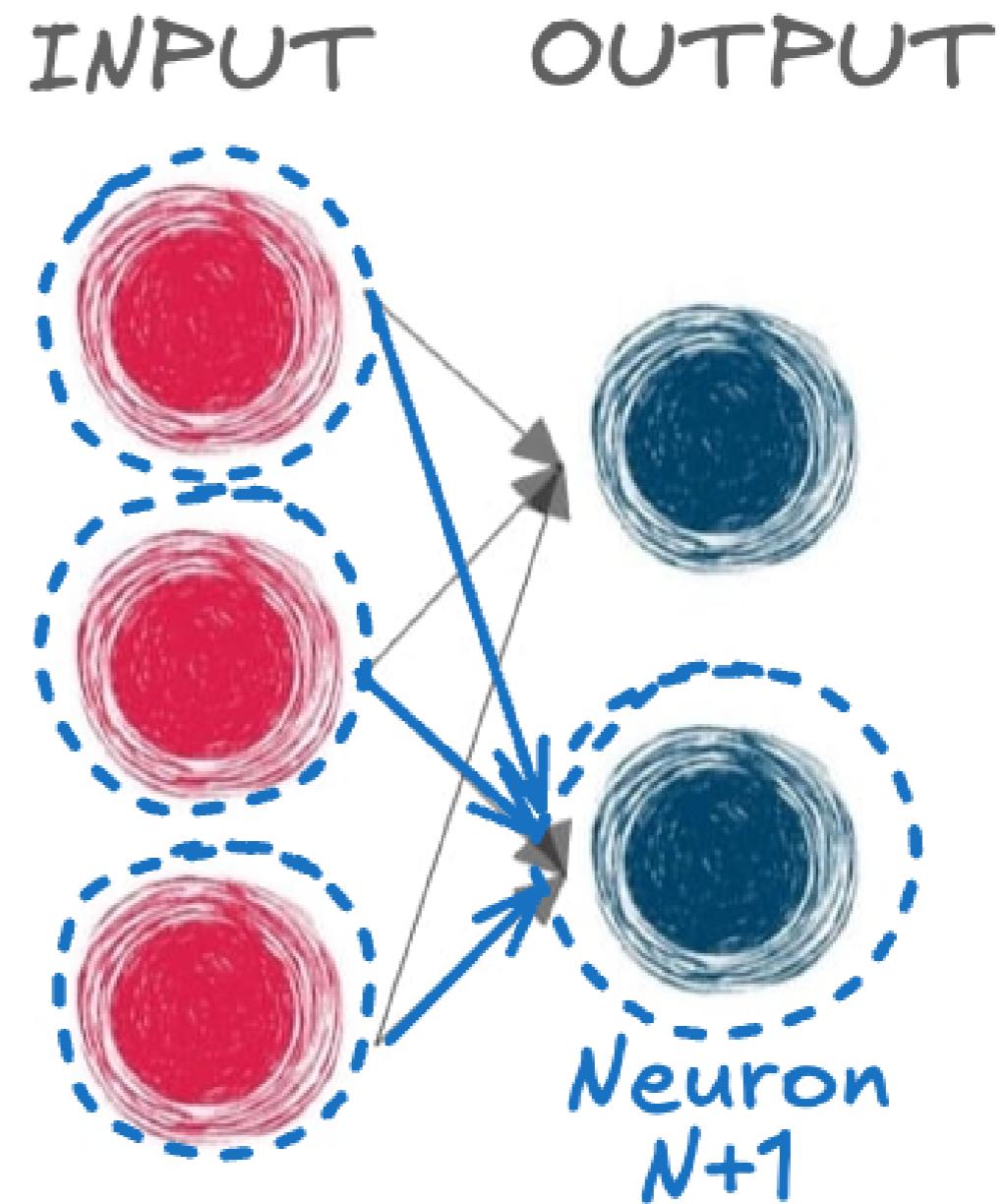
Layers are made of neurons

- Fully connected when each neuron links to all neurons in the previous layer
- A neuron in a linear layer:
 - Performs a linear operation using all neurons from the previous layer



Layers are made of neurons

- Fully connected when each neuron links to all neurons in the previous layer
- A neuron in a linear layer:
 - Performs a linear operation using **all neurons** from the previous layer
 - Has $N+1$ parameters: N from **inputs** and 1 for the **bias**



Parameters and model capacity

- More hidden layers = more parameters =
higher **model capacity**

Given the following model:

```
model = nn.Sequential(nn.Linear(8, 4),  
                      nn.Linear(4, 2))
```

Parameters and model capacity

- More hidden layers = more parameters = higher **model capacity**

Given the following model:

```
model = nn.Sequential(nn.Linear(8, 4),  
                      nn.Linear(4, 2))
```

Manual parameter calculation:

- First layer has 4 neurons, each neuron has 8+1 parameters. 9 times 4 = 36 parameters

Parameters and model capacity

- More hidden layers = more parameters = higher **model capacity**

Given the following model:

```
model = nn.Sequential(nn.Linear(8, 4),  
                      nn.Linear(4, 2))
```

Manual parameter calculation:

- First layer has 4 neurons, each neuron has $8+1$ parameters. $9 \times 4 = 36$ parameters

Parameters and model capacity

- More hidden layers = more parameters = higher **model capacity**

Given the following model:

```
model = nn.Sequential(nn.Linear(8, 4),  
                      nn.Linear(4, 2))
```

Manual parameter calculation:

- First layer has 4 neurons, each neuron has $8+1$ parameters. $9 \times 4 = 36$ parameters
- Second layer has 2 neurons, each neuron has $4+1$ parameters. $5 \times 2 = 10$ parameters

Parameters and model capacity

- More hidden layers = more parameters = higher **model capacity**

Given the following model:

```
model = nn.Sequential(nn.Linear(8, 4),  
                      nn.Linear(4, 2))
```

Manual parameter calculation:

- First layer has 4 neurons, each neuron has $8+1$ parameters. $9 \times 4 = 36$ parameters
- Second layer has 2 neurons, each neuron has $4+1$ parameters. $5 \times 2 = 10$ parameters
- $36 + 10 = 46$ learnable parameters

Parameters and model capacity

- More hidden layers = more parameters = higher **model capacity**

Given the following model:

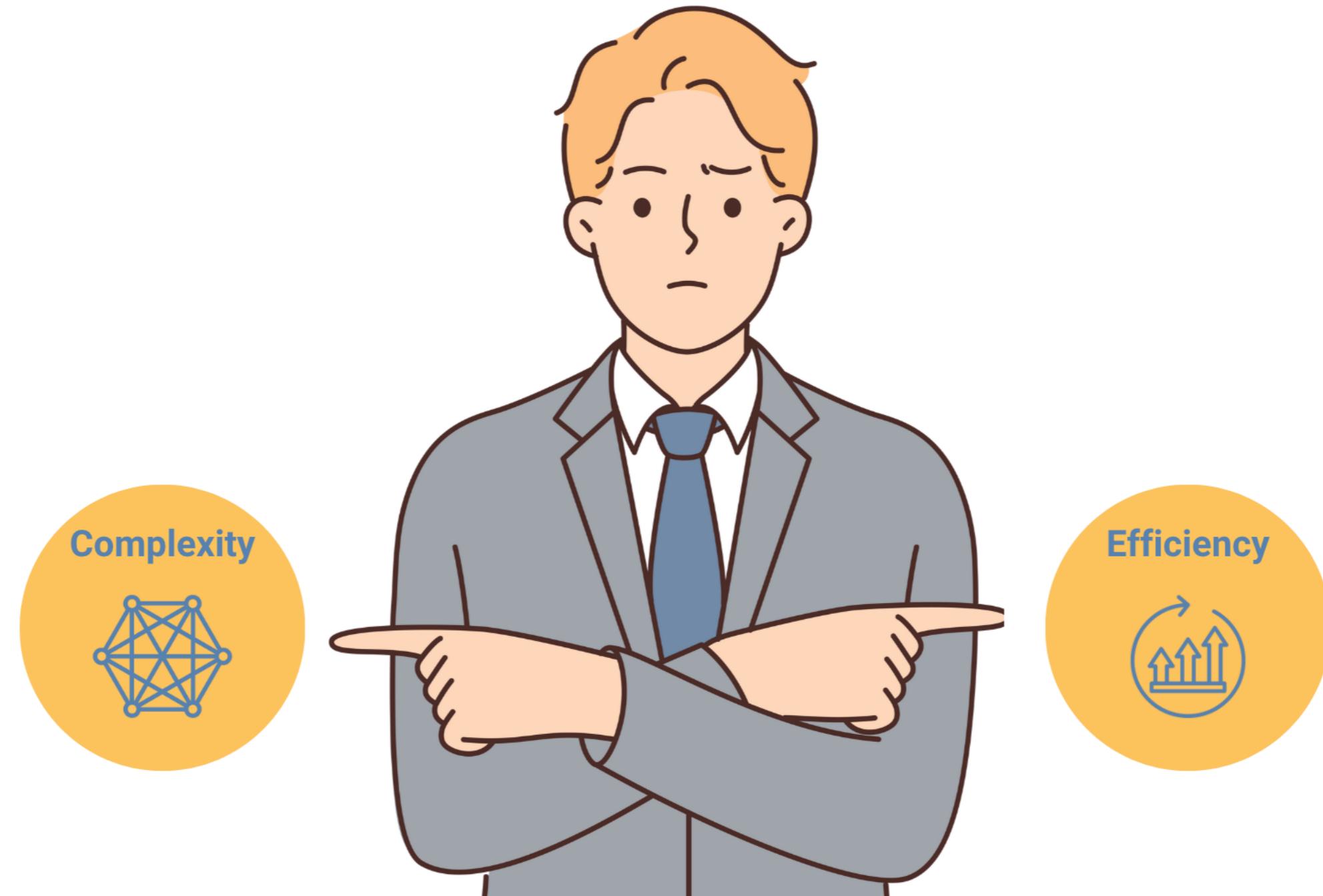
```
model = nn.Sequential(nn.Linear(8, 4),  
                      nn.Linear(4, 2))
```

Using PyTorch:

- `.numel()` : returns the number of elements in the tensor

```
total = 0  
for parameter in model.parameters():  
    total += parameter.numel()  
print(total)
```

Balancing complexity and efficiency



Let's practice!

INTRODUCTION TO DEEP LEARNING WITH PYTORCH