Introduction to deep learning with PyTorch

INTRODUCTION TO DEEP LEARNING WITH PYTORCH

Jasmin Ludolf
Senior Data Science Content Developer, DataCamp

Deep learning is everywhere!

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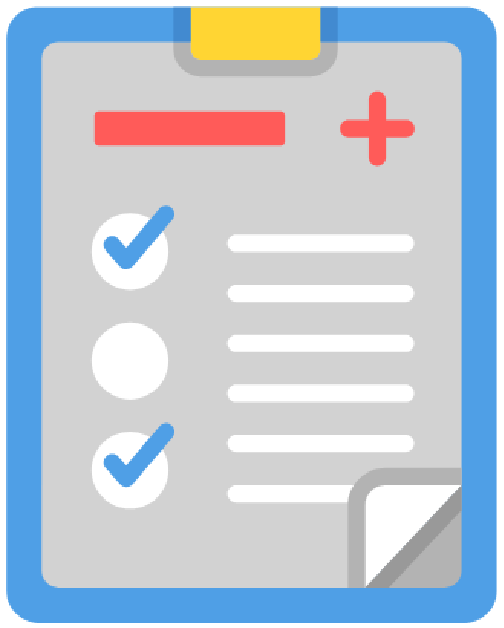
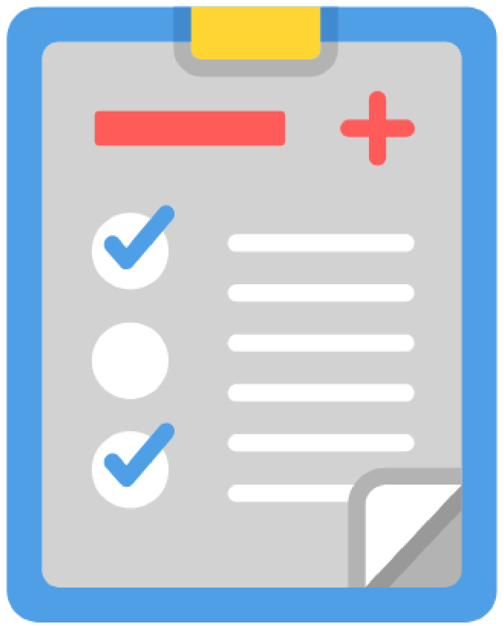
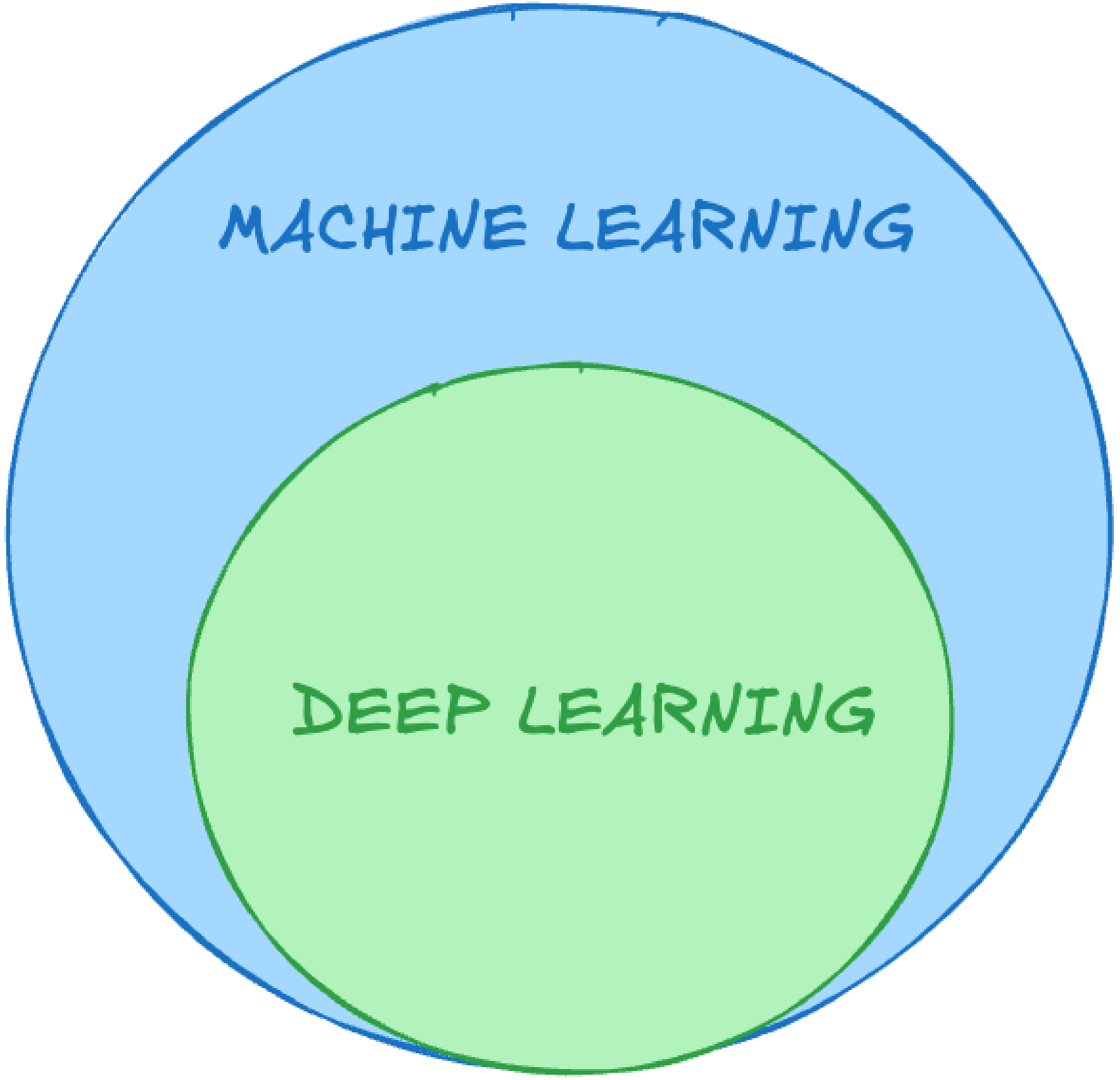
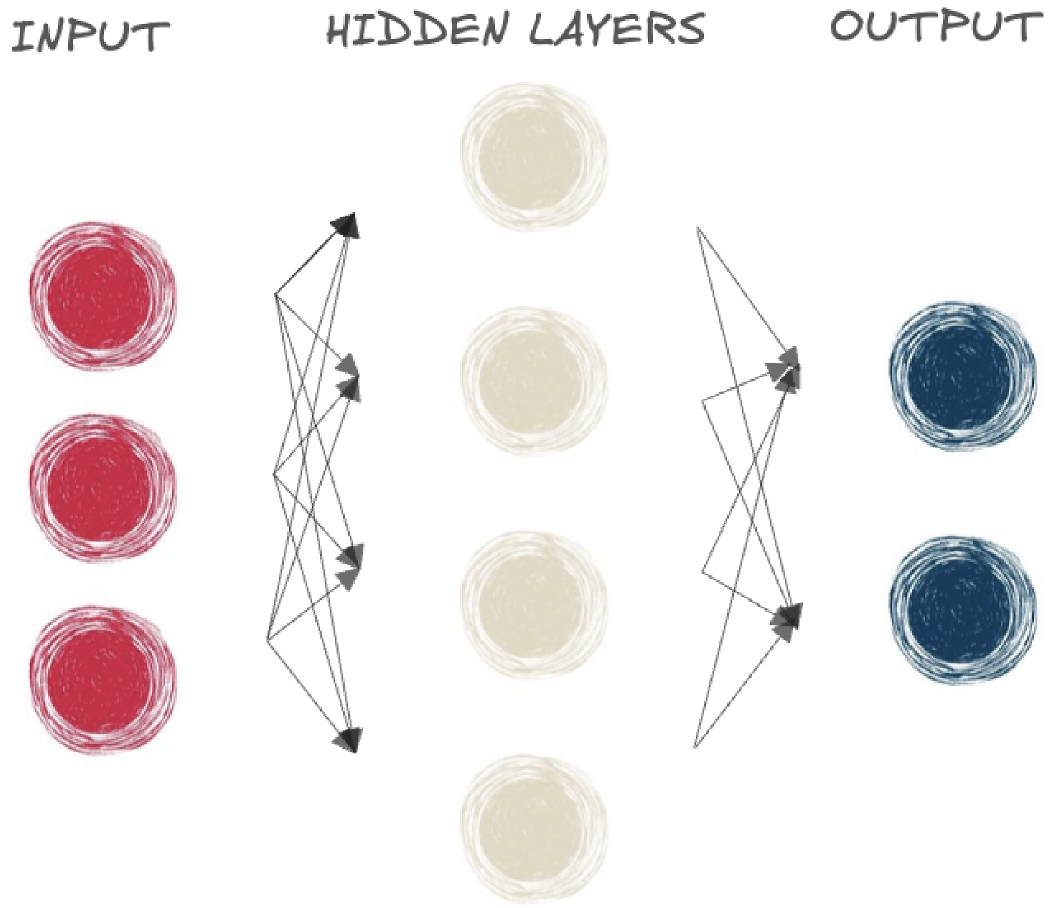


Deep learning is everywhere!

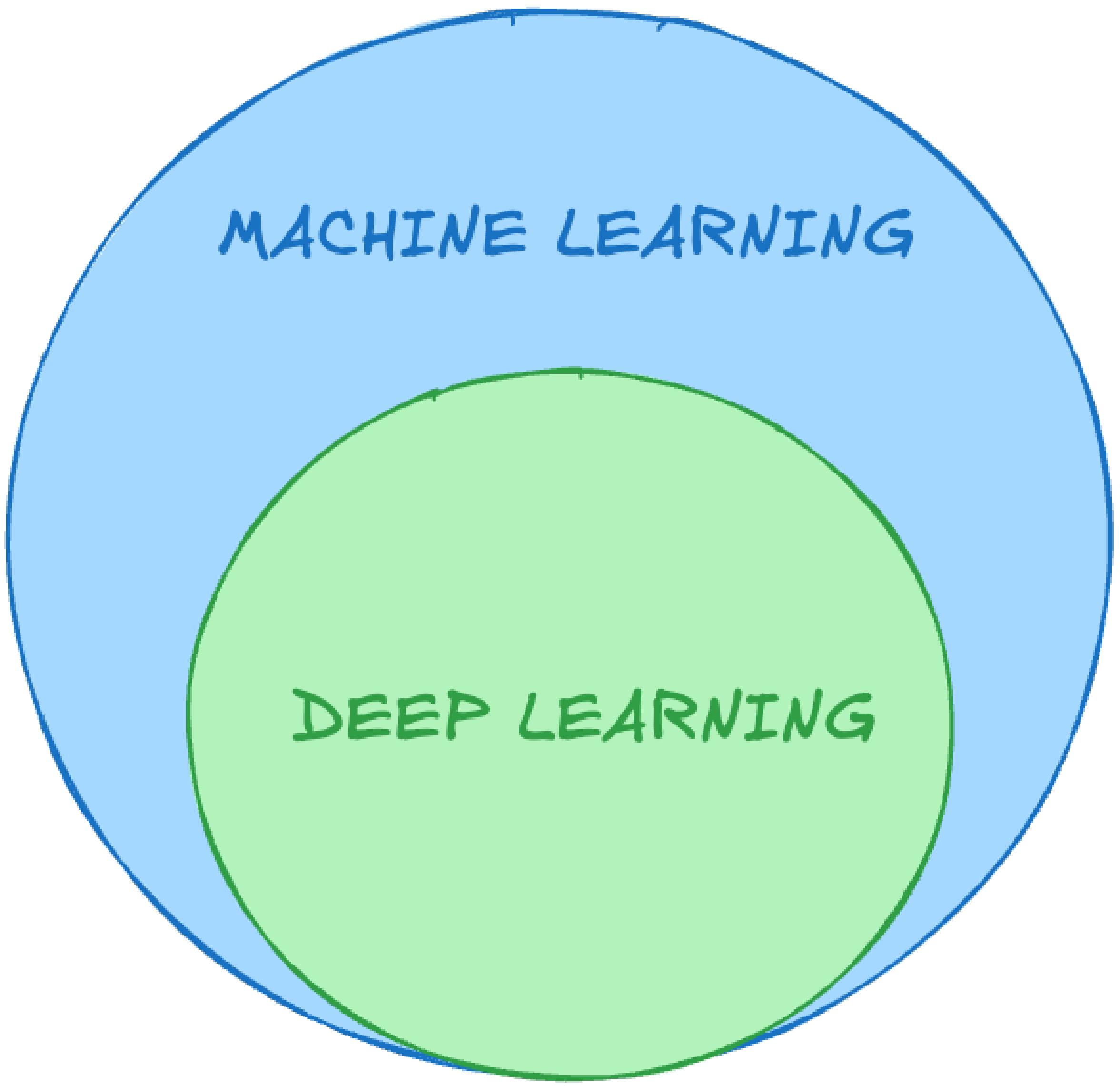


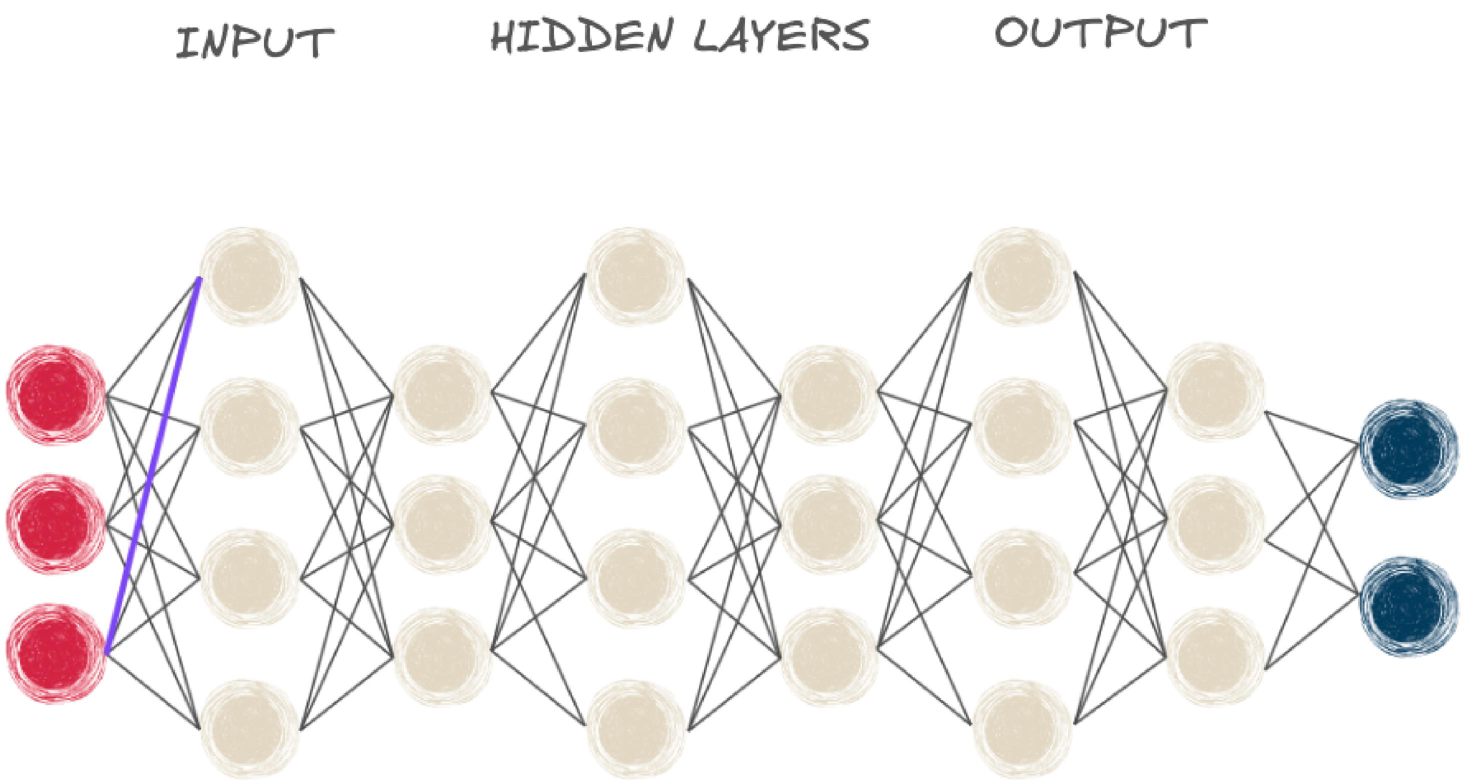
What is deep learning?





What is deep learning?



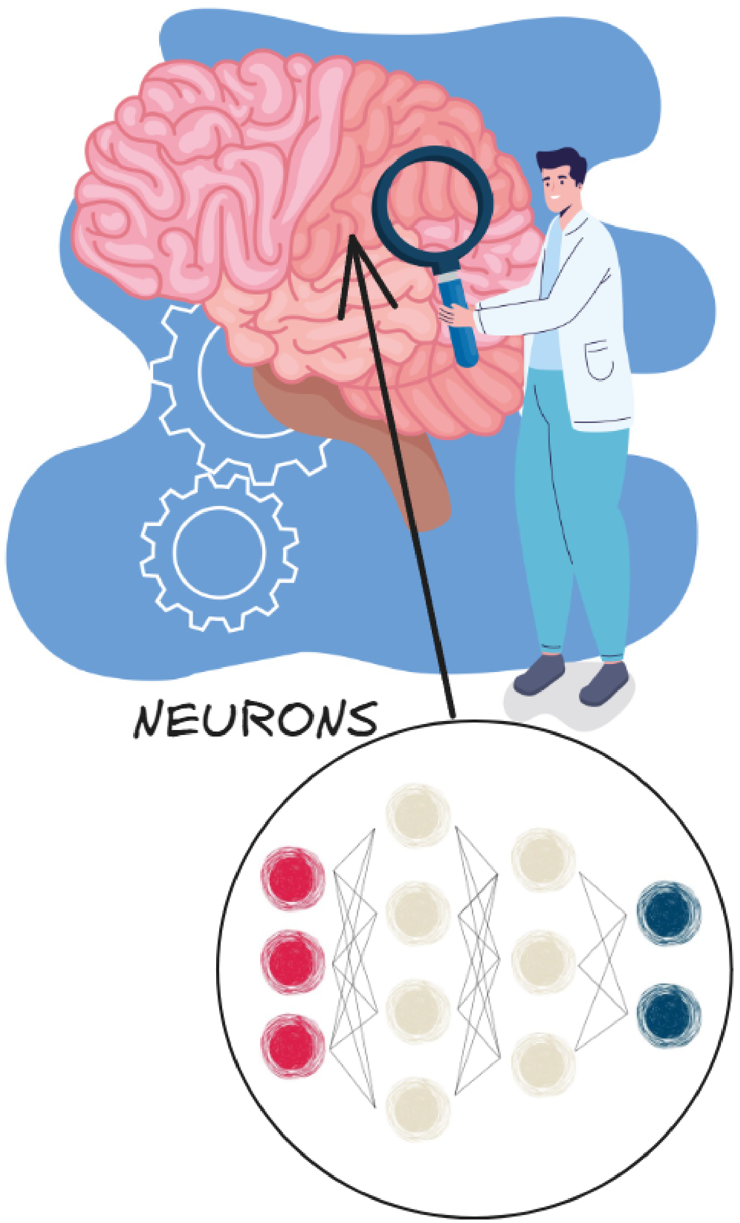


Deep learning networks

- 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

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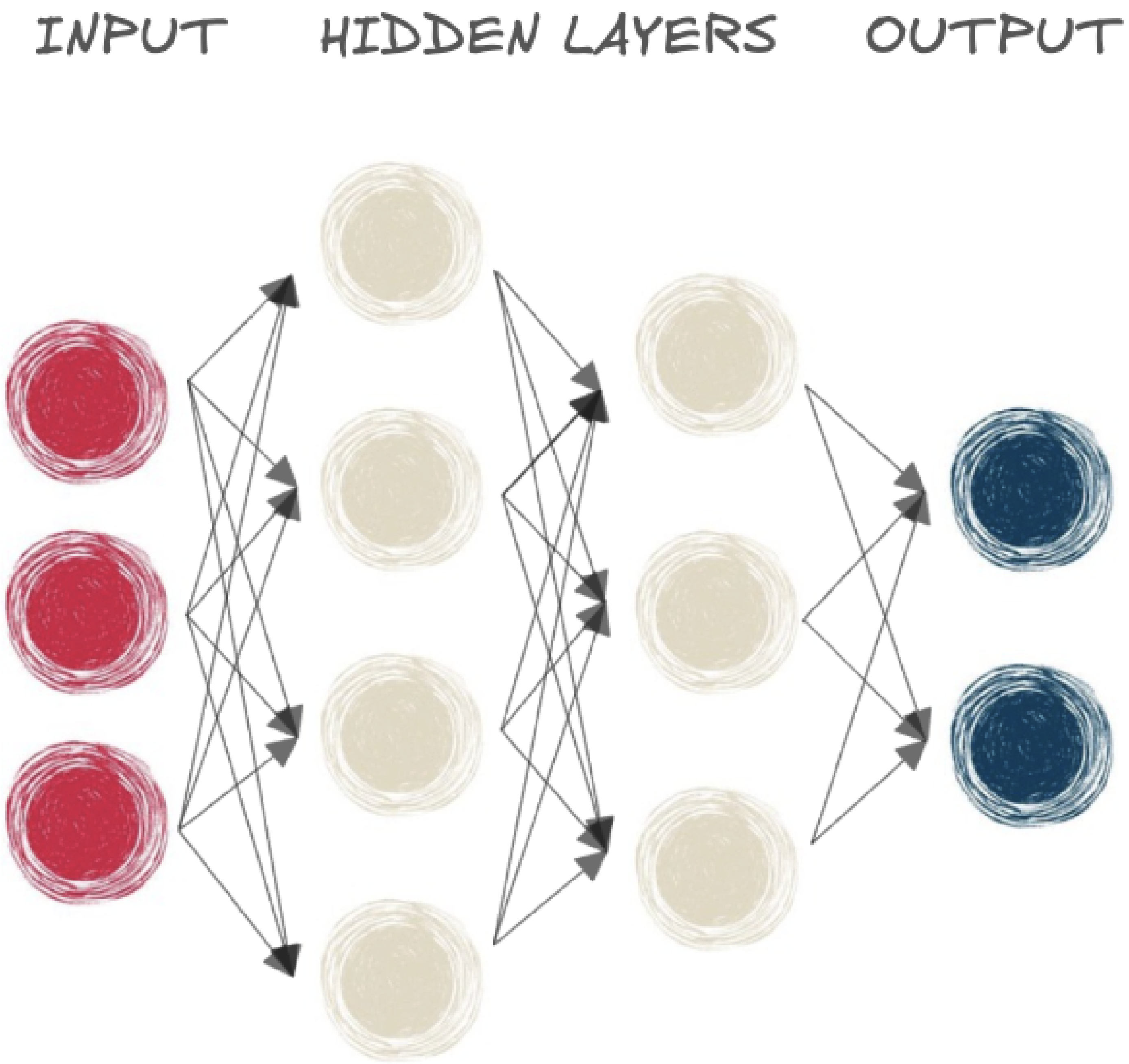
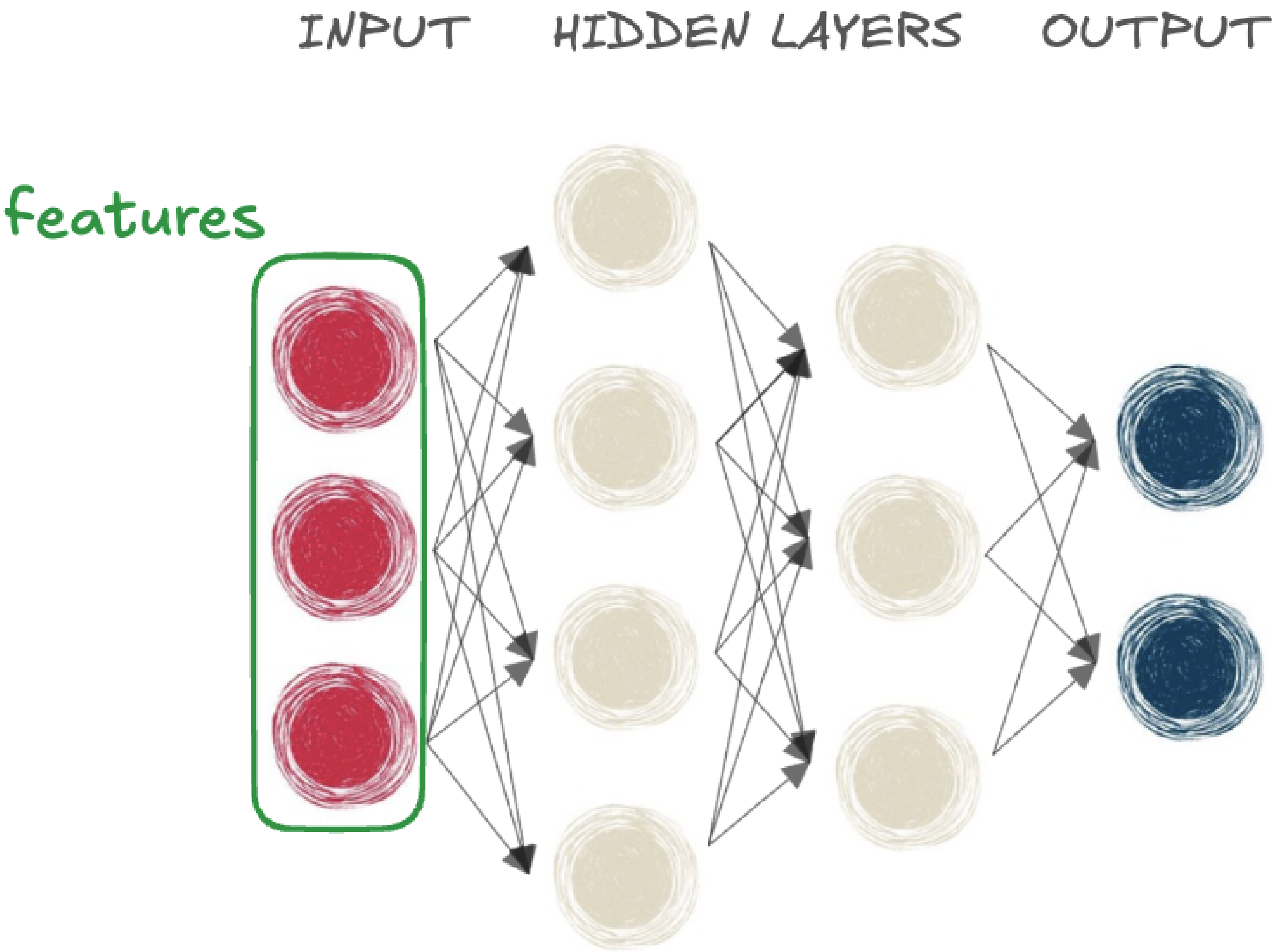
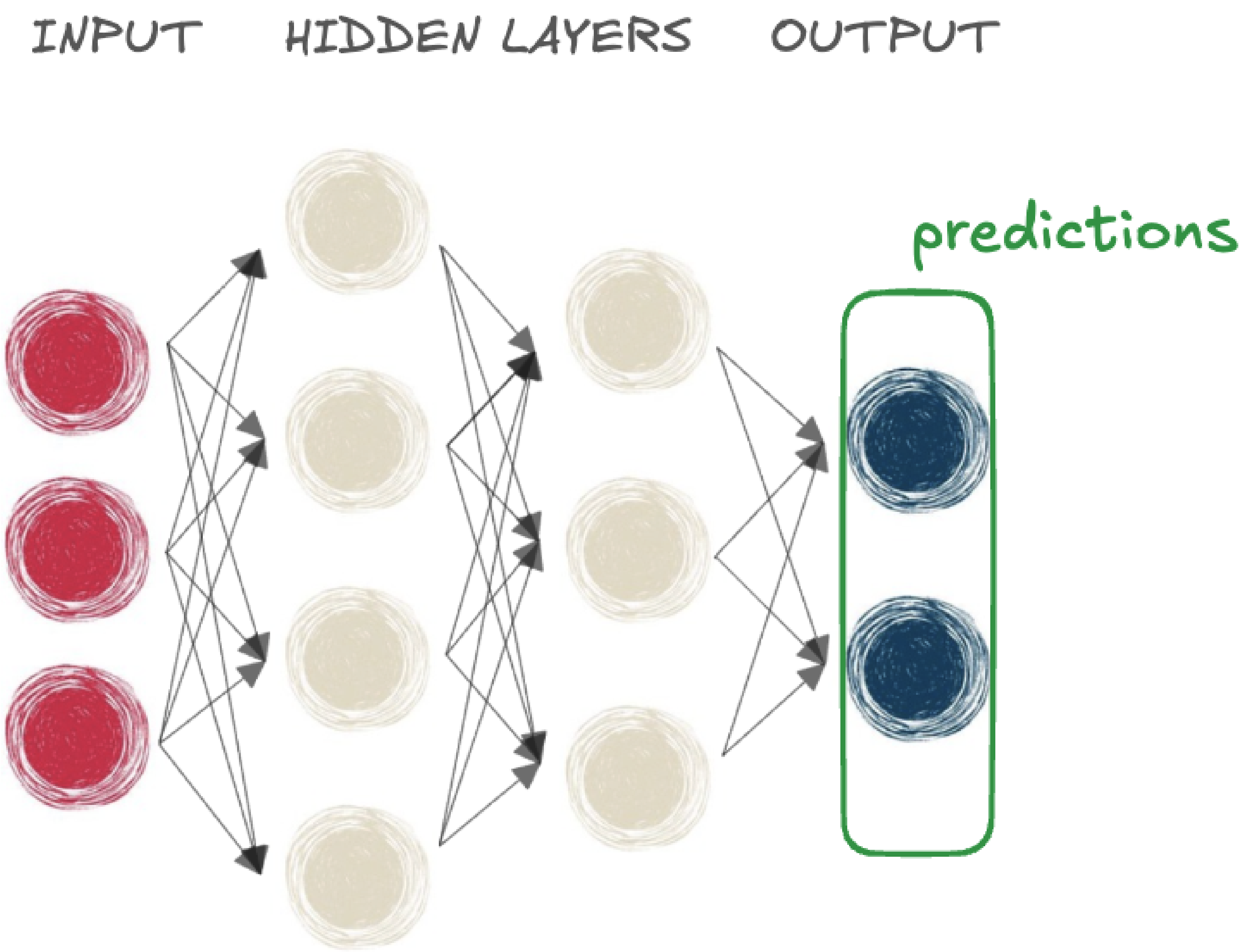
Neural network layers



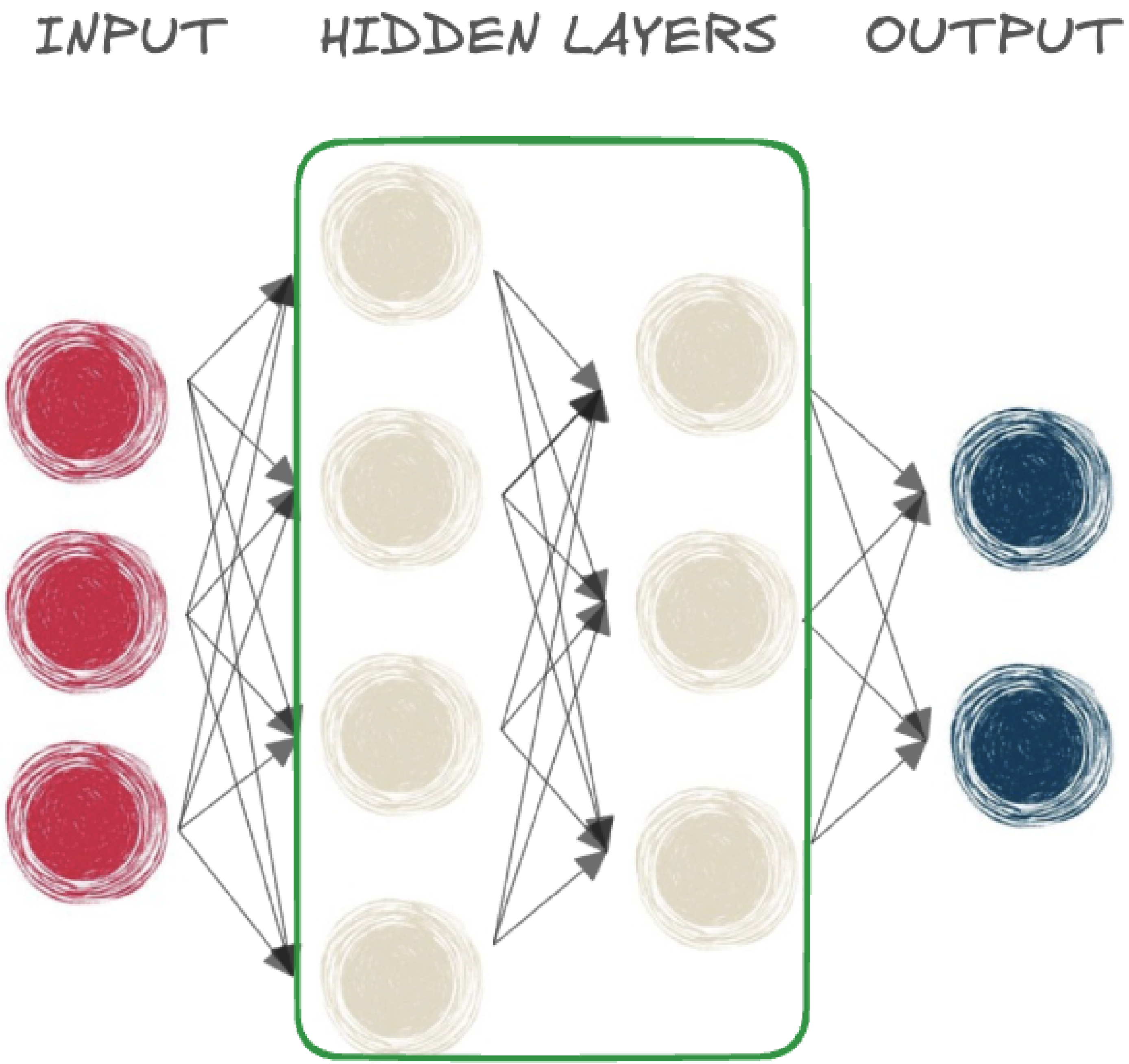
Neural network layers



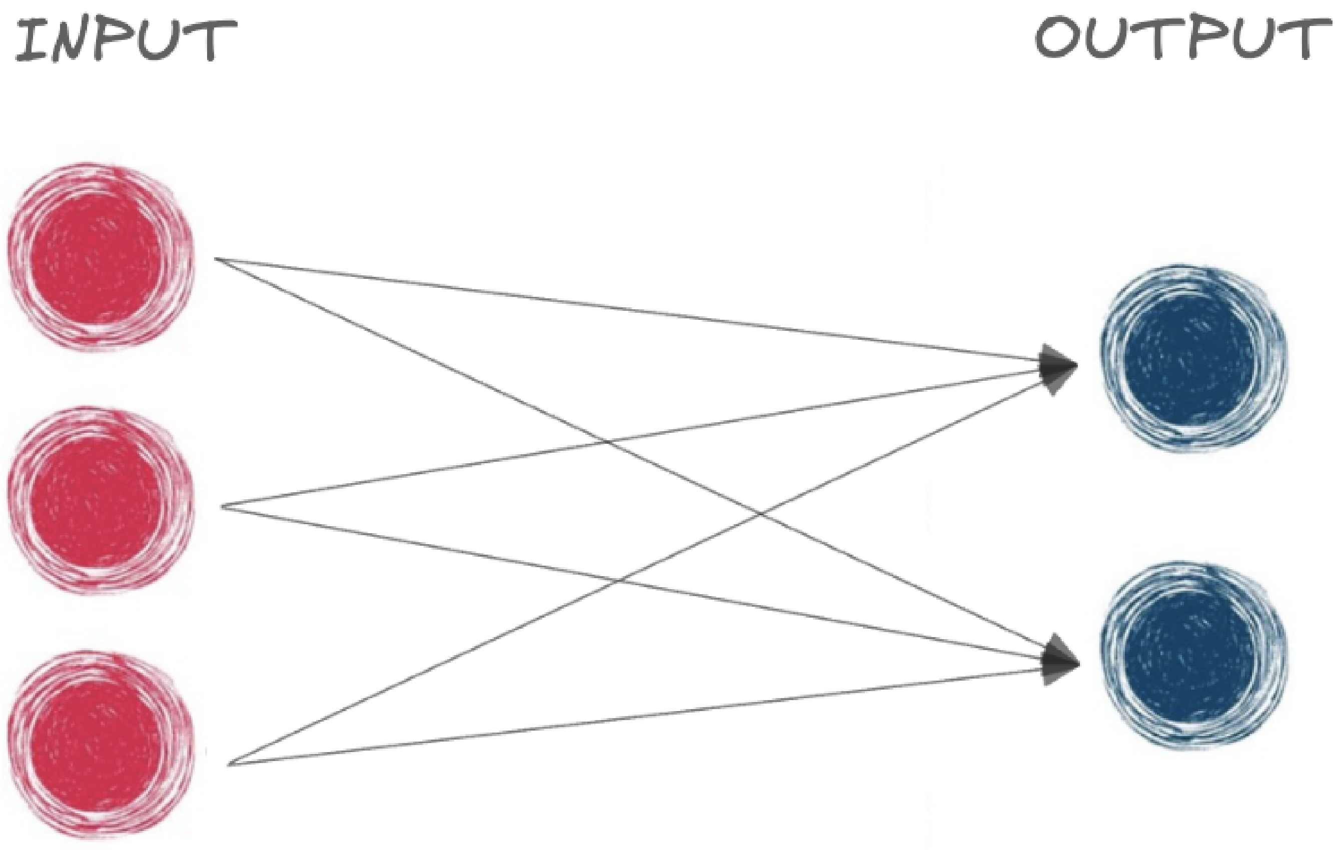
Neural network layers



Neural network layers



Our first neural network



- Fully connected network
- Equivalent to a linear model

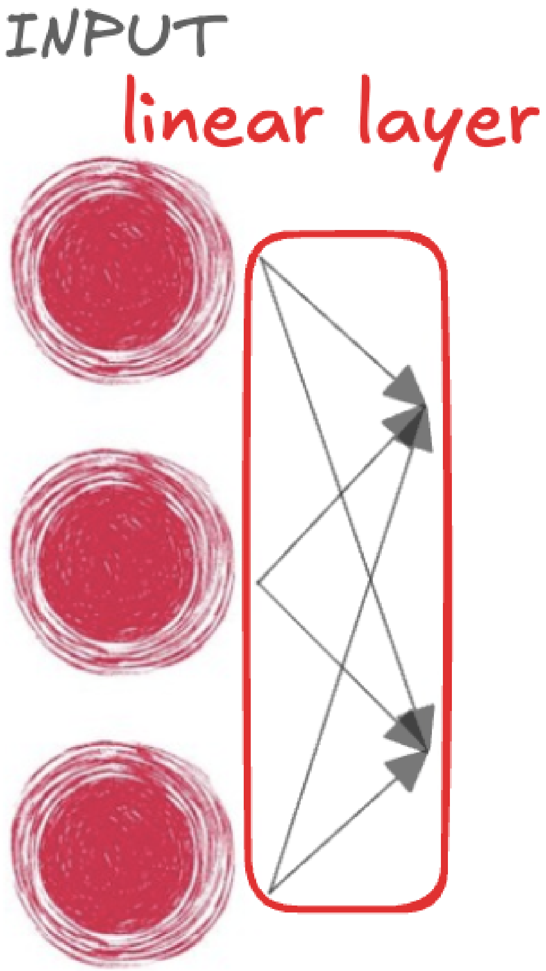
Designing a neural network


```python
# 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




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

# Create input_tensor with three features
input_tensor = torch.tensor(
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# Define our linear layer
linear_layer = nn.Linear(
                         in_features=3,
                         out_features=2
                         )
```
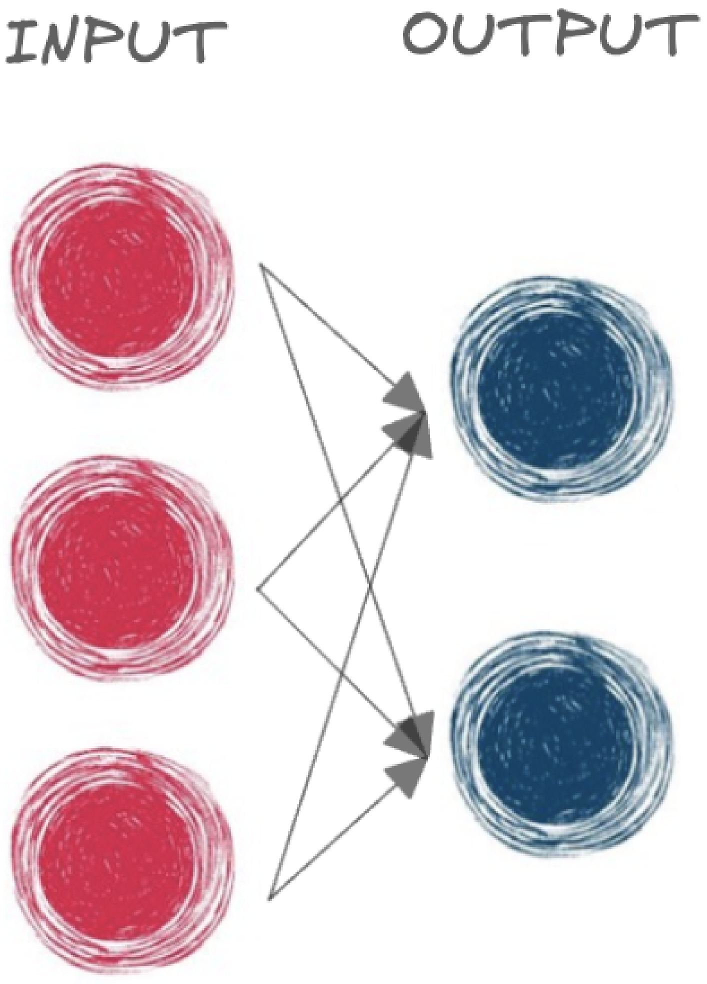

Designing a neural network

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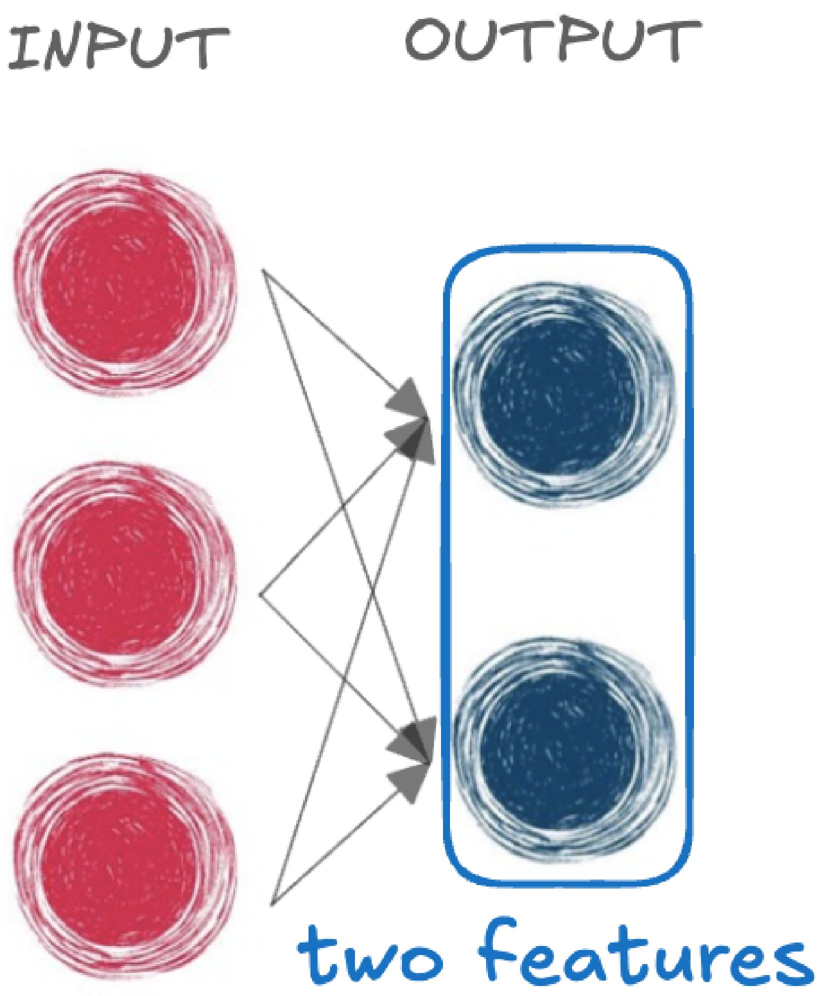
# Define our linear layer
linear_layer = nn.Linear(
                         in_features=3,
                         out_features=2
                         )


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

Designing a neural network

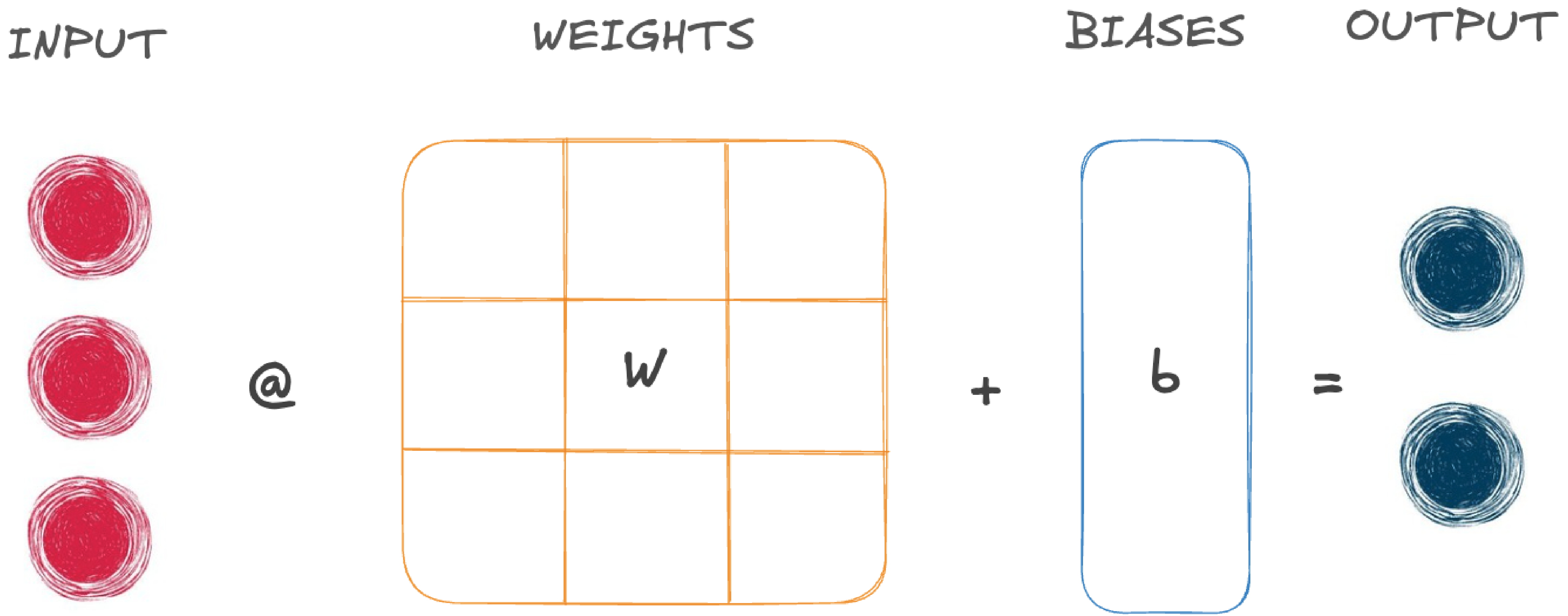



```
# Pass input through linear layer
output = linear_layer(input_tensor)
print(output)
```

```
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)
```

- Reflects the importance of different features

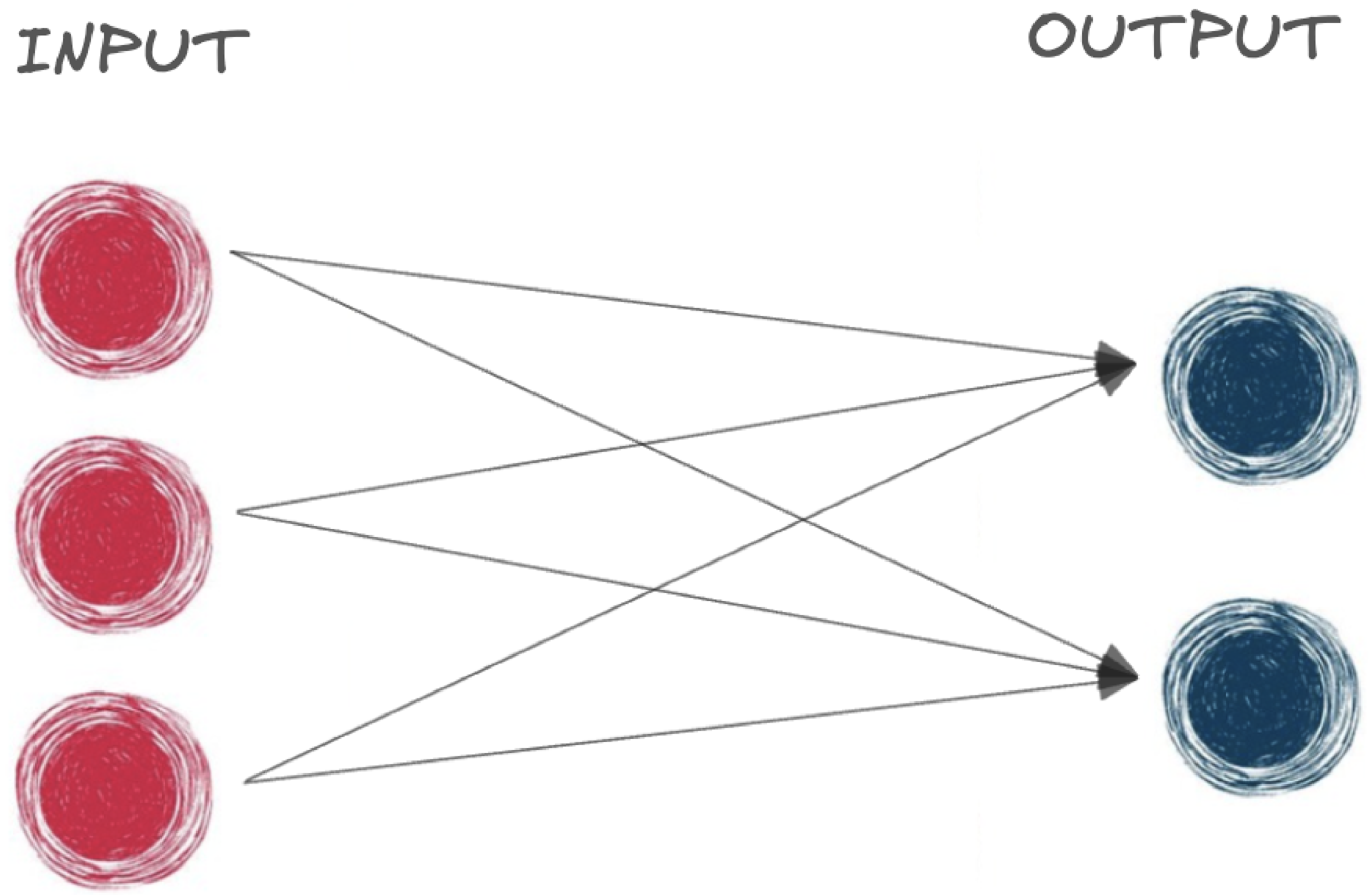
- `.bias`

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

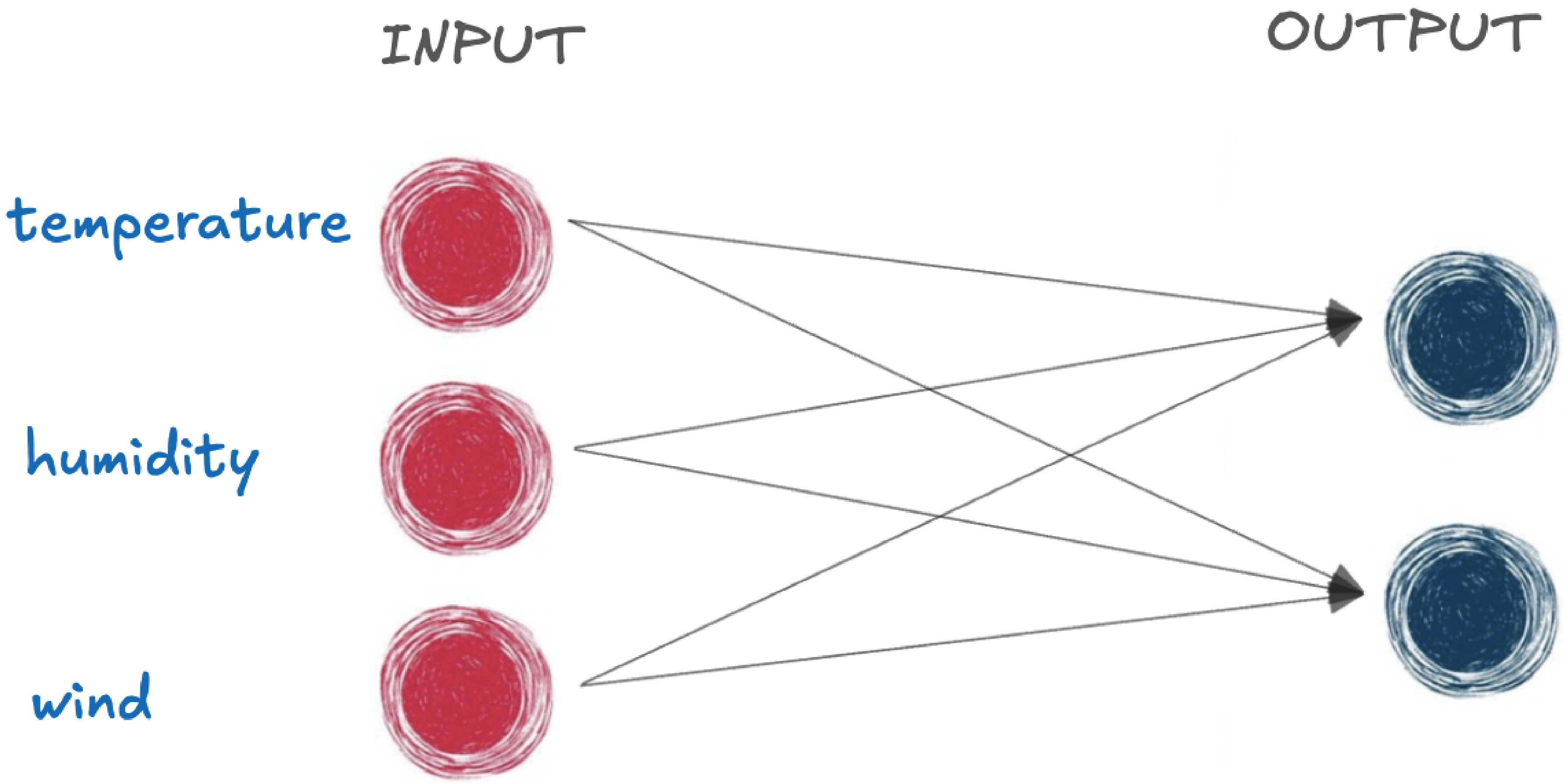
```
Parameter containing:
tensor([0.0310, 0.1537], requires_grad=True)
```

- Provides the neuron with a baseline output

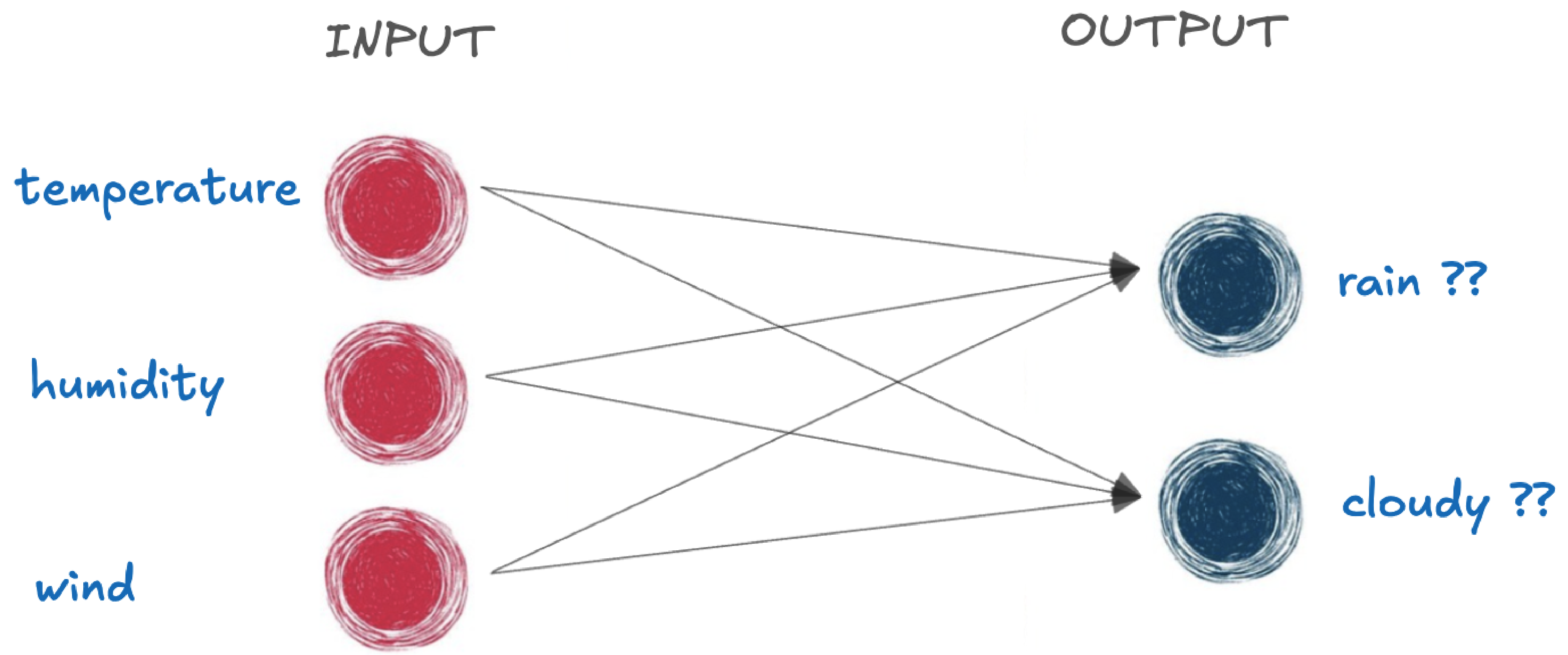
A fully connected network in action



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

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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)
)
```

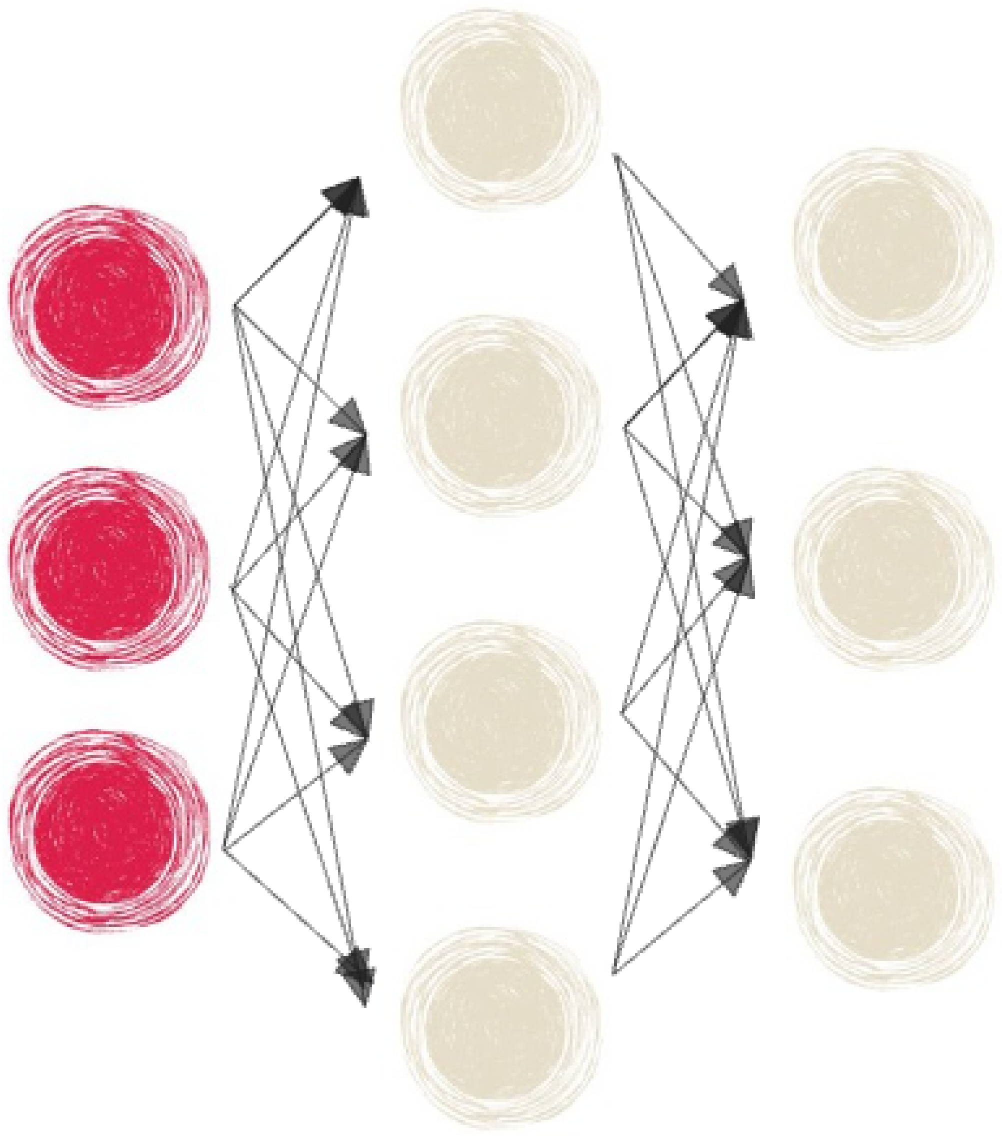
- Input is passed through the linear layers
- Layers within `nn.Sequential()` are hidden layers

Stacking layers with nn.Sequential()

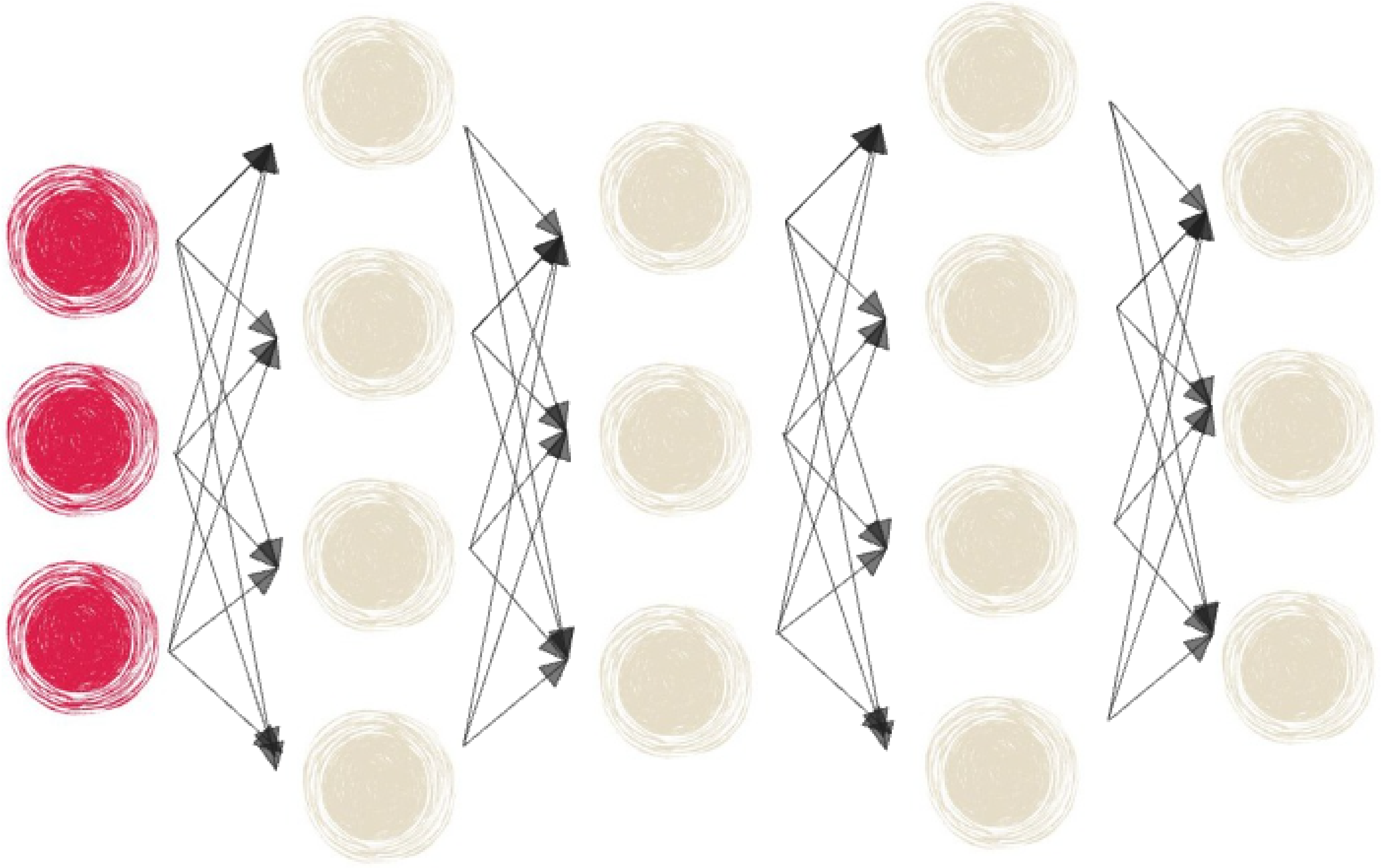
```
# Create network with three linear layers
model = nn.Sequential(
    nn.Linear(n_features, 8), # n_features represents number of input features
    nn.Linear(8, 4),
    nn.Linear(4, n_classes) # n_classes represents the number of output classes
)
```

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

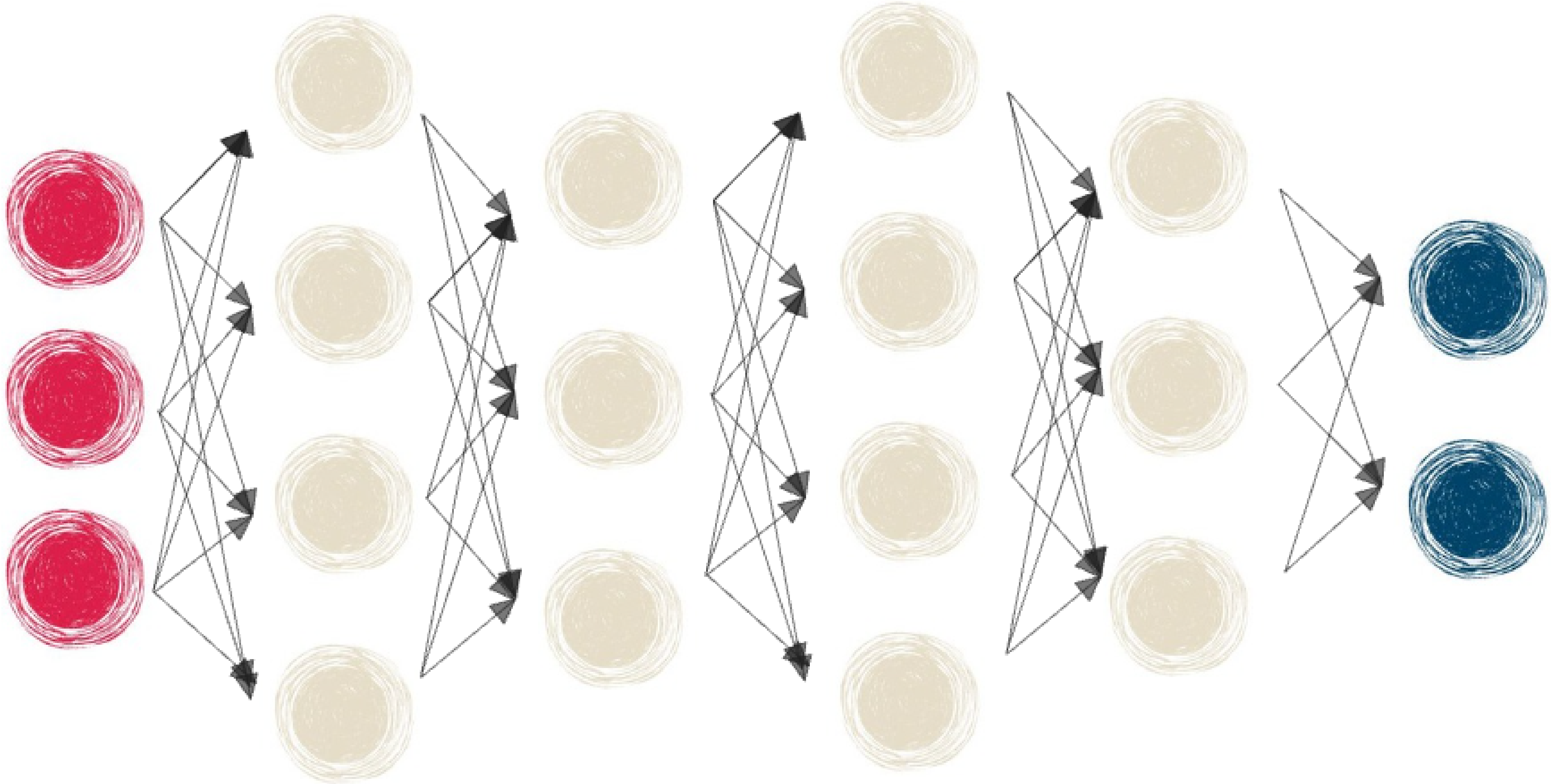
Adding layers



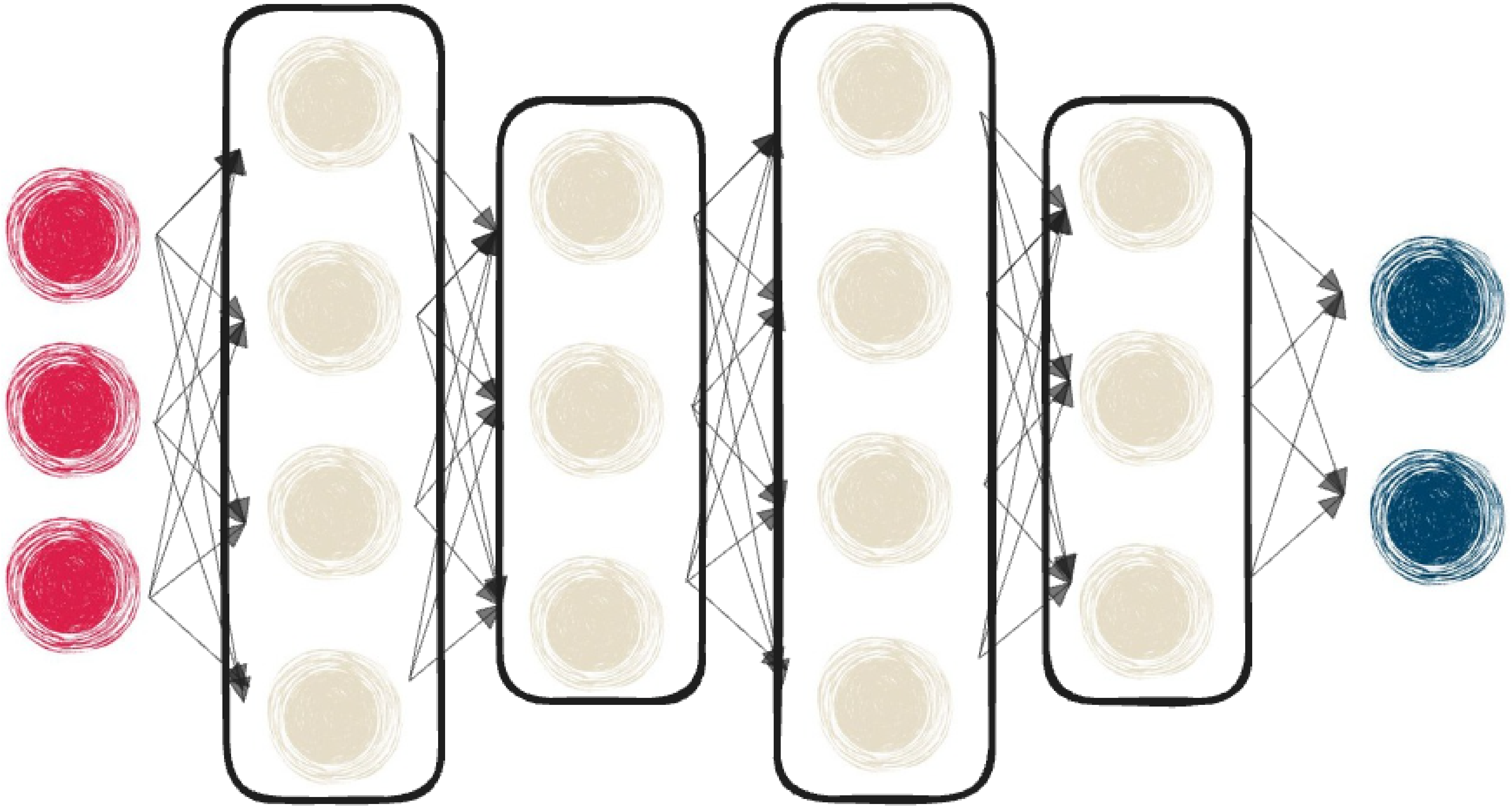
Adding layers



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**

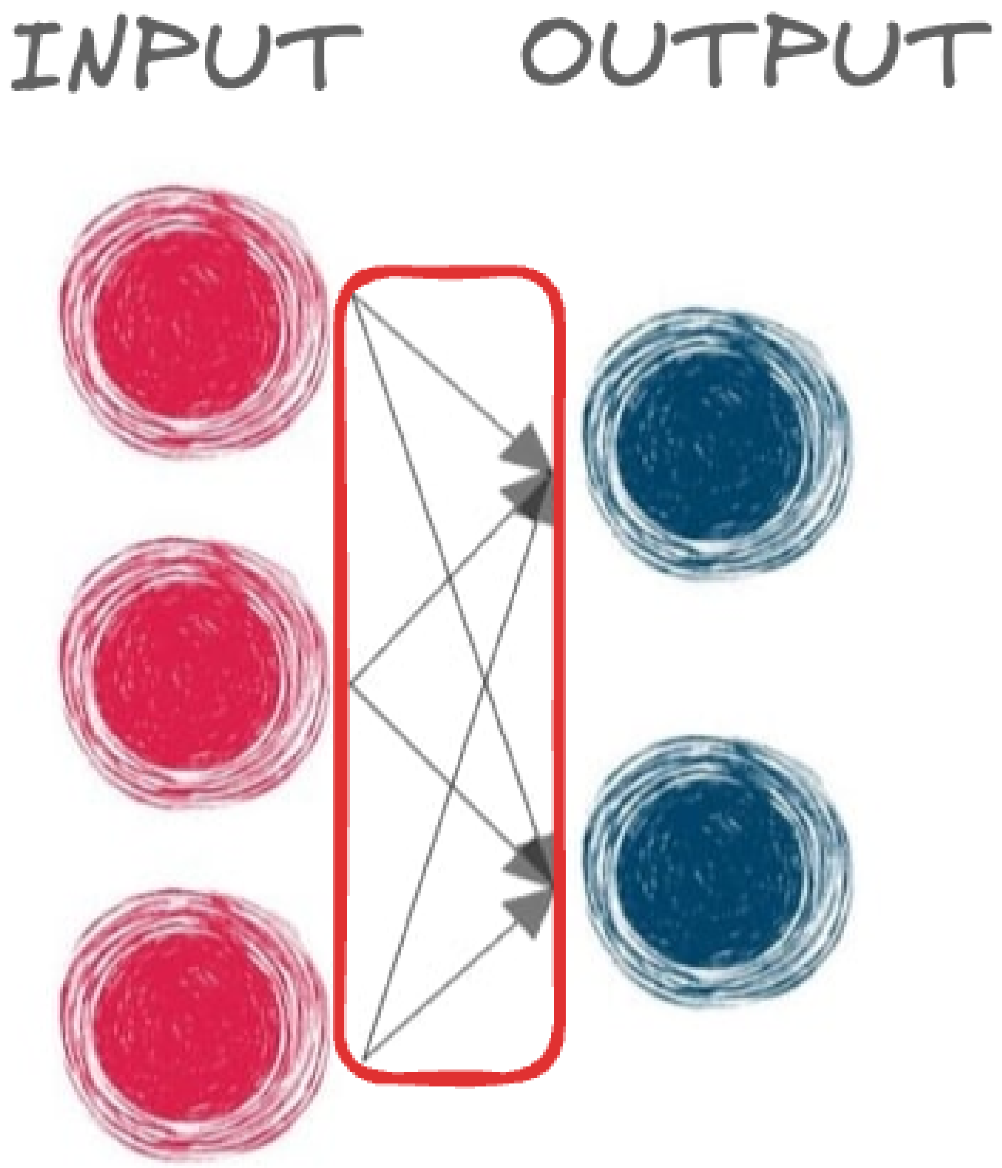
Adding layers

```
# 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

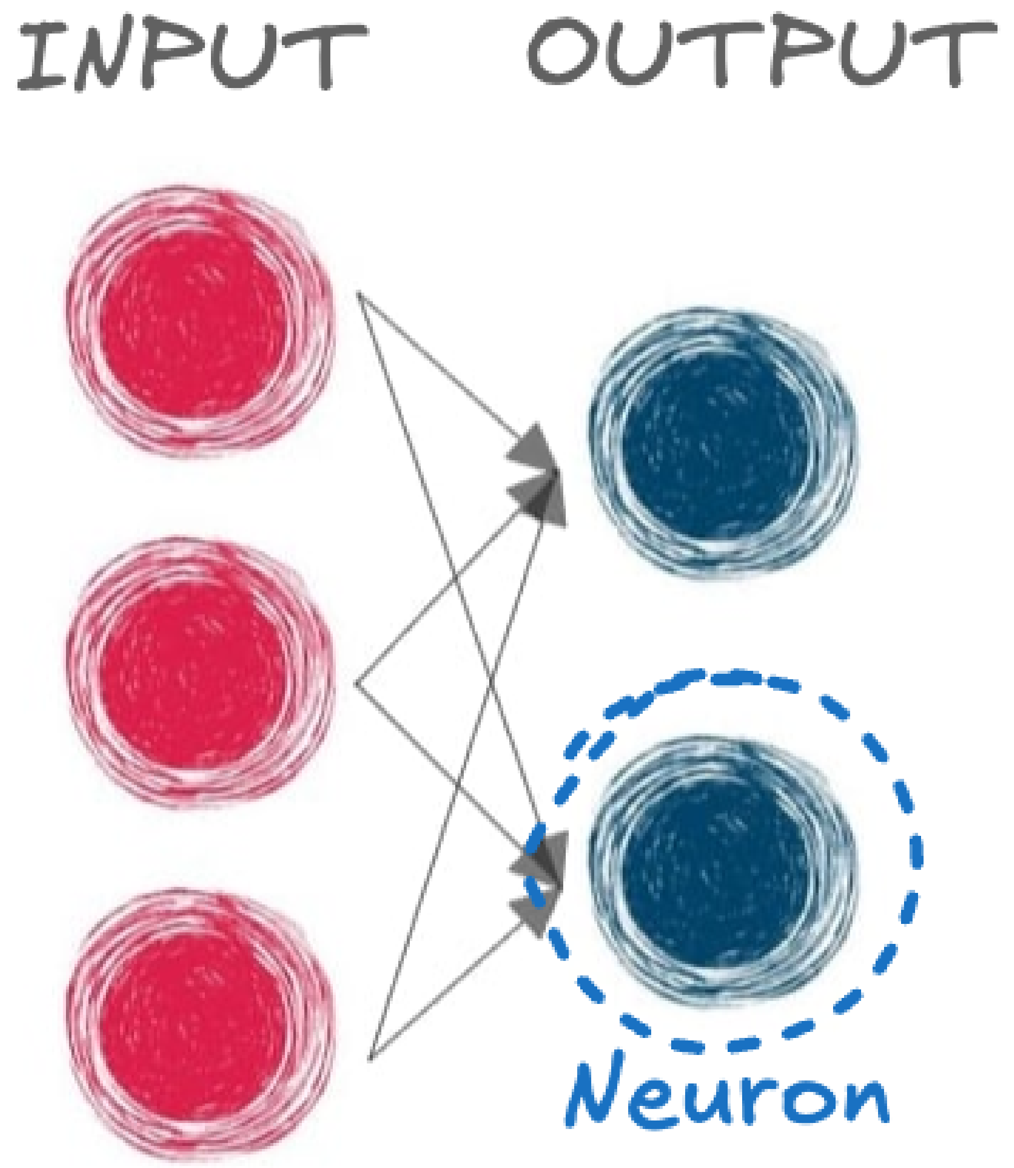
- **Fully connected** when each neuron links to all neurons in the previous layer



Layers are made of neurons

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

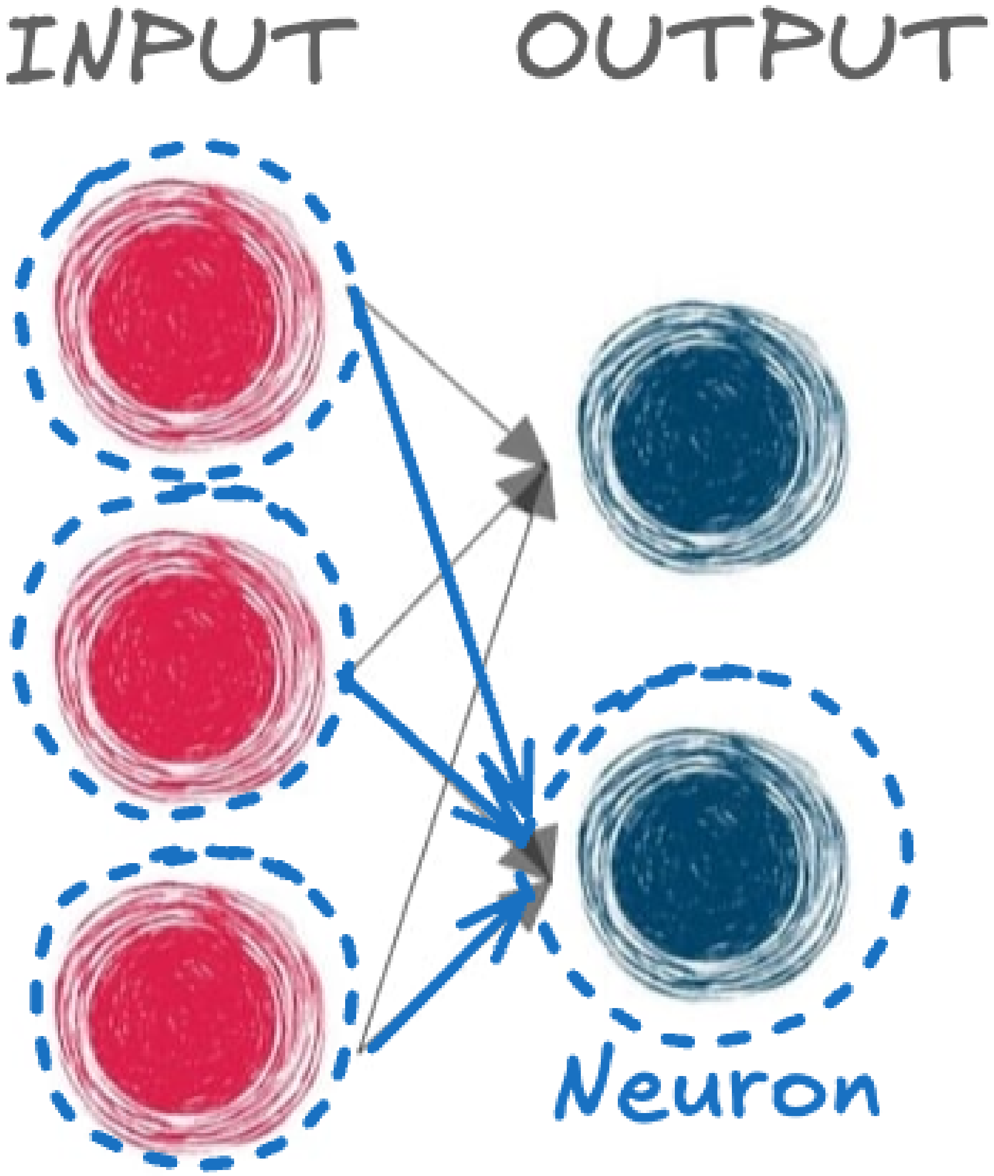
- A neuron in a linear layer:



Layers are made of neurons

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

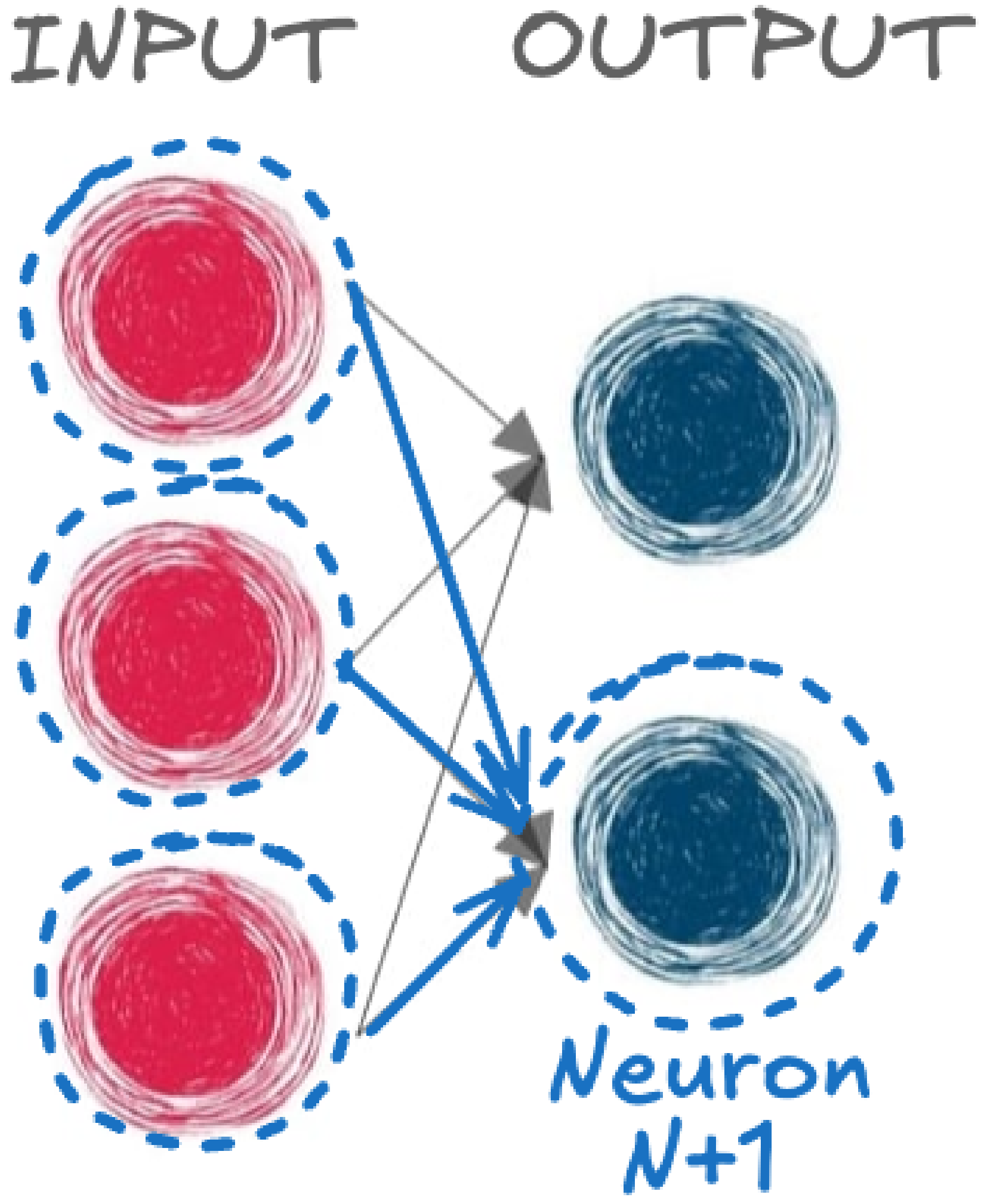
- A neuron in a linear layer:
  - Performs a linear operation using **all neurons** from the previous layer



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))
```

+1

Manual parameter calculation:

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

Parameters and model capacity

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Given the following model:

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

+1

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))
```

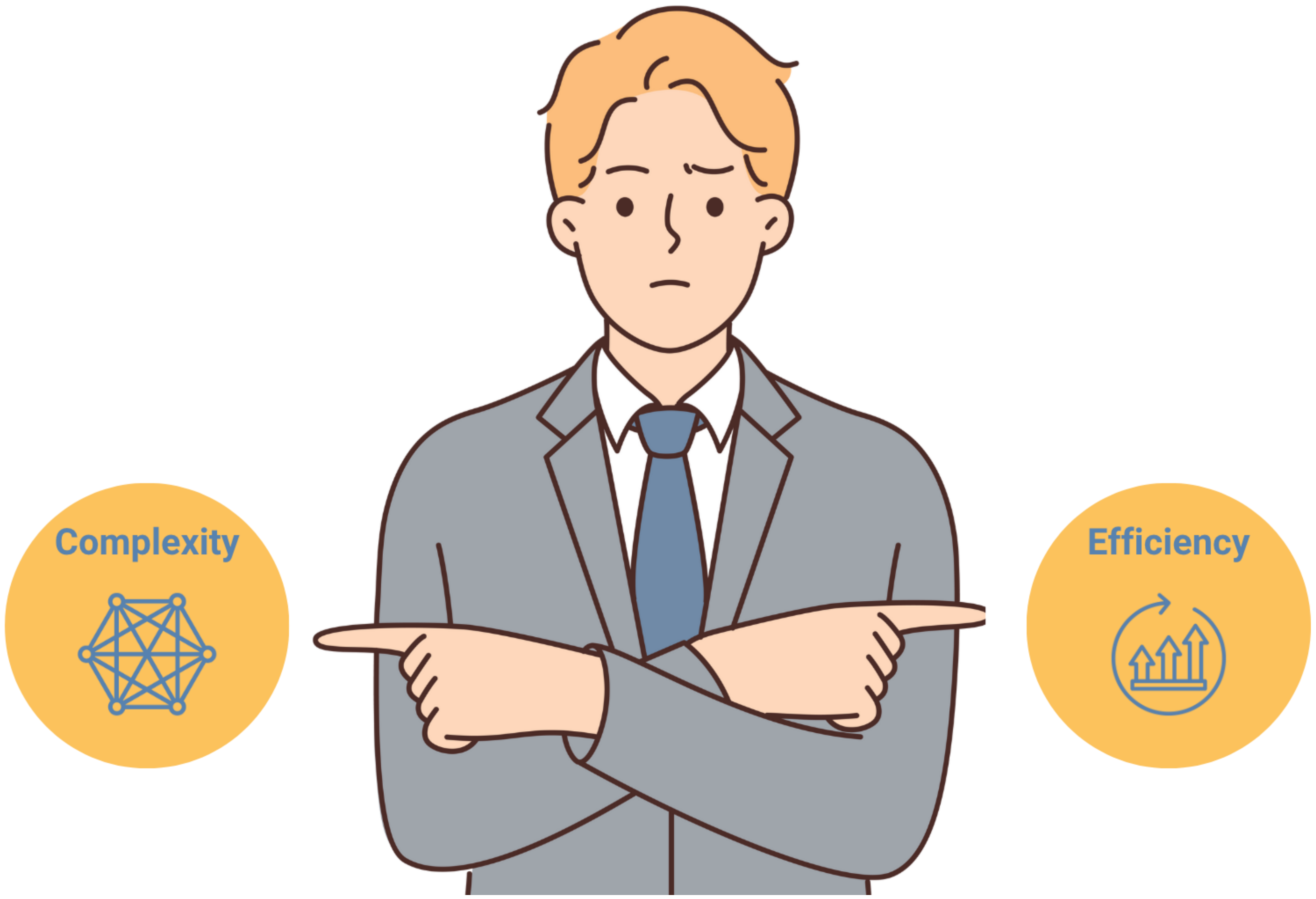
Using PyTorch:

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

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

```
46
```

Balancing complexity and efficiency



Let's practice!

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