MAI4CAREU

Master programmes in Artificial Intelligence 4 Careers in Europe

University of Ruse

INTELLIGENT COMPUTER SYSTEMS

Svetlana Stefanova

September, 2022

Co-financed by the European Union
Connecting Europe Facility

This Master is run under the context of Action No 2020-EU-IA-0087, co-financed by the EU CEF Telecom under GA nr. INEA/CEF/ICT/A2020/2267423

LECTURE 12

DEEP NEURAL NETWORKS

1. Introduction
2. Types of deep neural networks

Co-financed by the European Union
Connecting Europe Facility

This Master is run under the context of Action No 2020-EU-IA-0087, co-financed by the EU CEF Telecom under GA nr. INEA/CEF/ICT/A2020/2267423

CONTENT 1

Definition

Deep NN (Deep-Learning) differ from the more common shallow NN by the number of layers through which the data passes in a multi-level pattern recognition process.

With more than 3 layers (including input and output) networks qualify as "**deep**". A term that means more than 1 hidden layer.

This Master is run under the context of Action No 2020-EU-IA-0087, co-financed by the EU CEF Telecom under GA nr. INEA/CEF/ICT/A2020/2267423

CONTENT 1

Feature hierarchy

In deep learning networks, each layer of nodes is trained on a separate set of features based on the output of the previous layer.

The further one progresses in the NN, the more complex the features that the nodes can recognize are, as they merge and combine features from the previous layer.

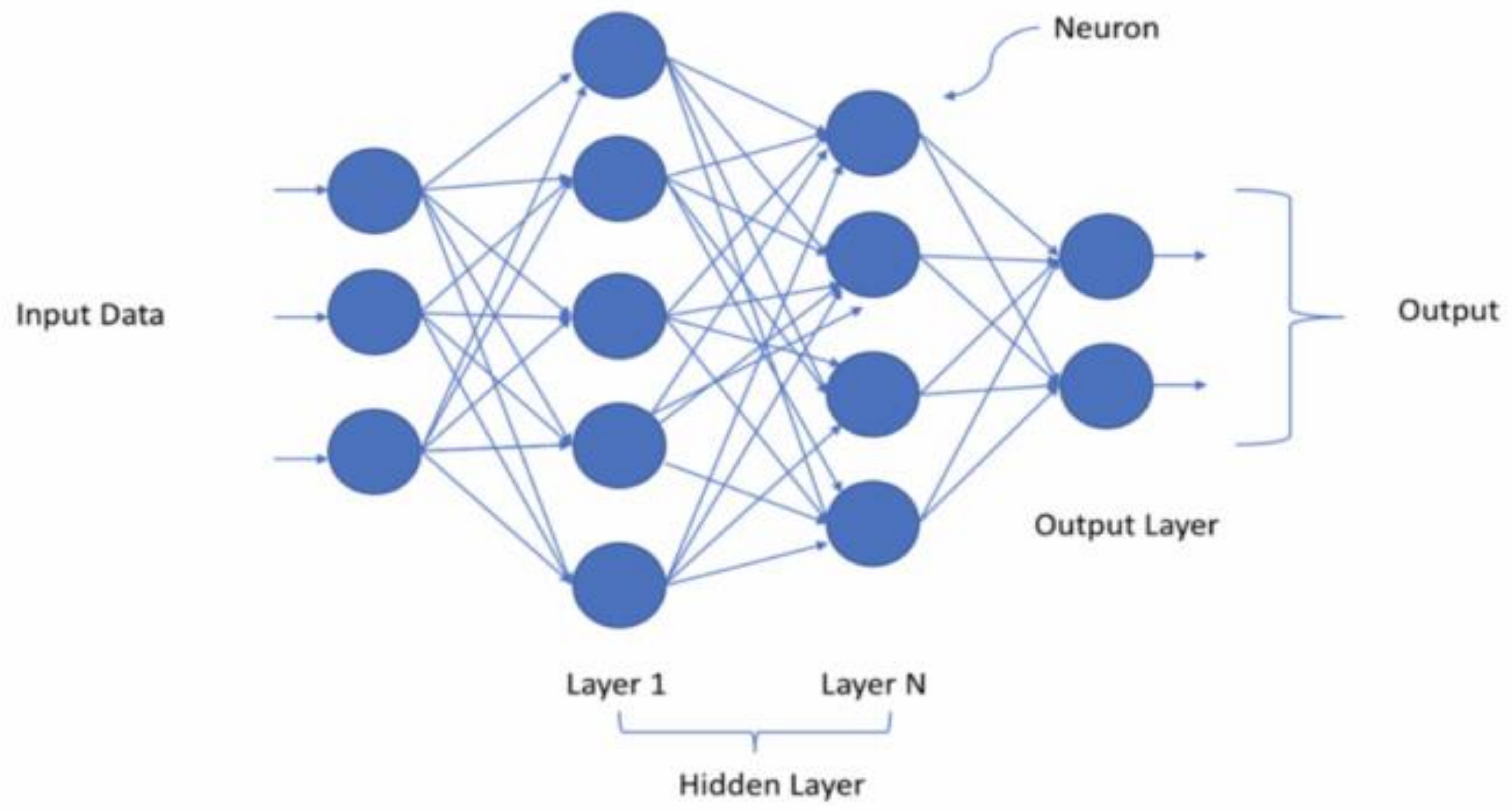
This is known as a **feature hierarchy** (a hierarchy of increasing complexity and abstraction). This makes deep networks capable of handling large arrays with billions of parameters that pass through non-linear functions.

Co-financed by the European Union
Connecting Europe Facility

This Master is run under the context of Action No 2020-EU-IA-0087, co-financed by the EU CEF Telecom under GA nr. INEA/CEF/ICT/A2020/2267423

CONTENT 1

Deep NN architecture



Co-financed by the European Union
Connecting Europe Facility

This Master is run under the context of Action
No 2020-EU-IA-0087, co-financed by the EU CEF Telecom
under GA nr. INEA/CEF/ICT/A2020/2267423

CONTENT 1

Deep NN function

Although deep learning algorithms are self-learning, they depend on the structure of the NN.

- During the multilevel training process, the algorithms use:
- unknown elements in the input distribution for feature extraction;
- object grouping;
- discovering useful data patterns.

Although no network is considered perfect, some algorithms are better suited for specific tasks. In order to choose the right ones, at least the main ones should be well known.

Co-financed by the European Union
Connecting Europe Facility
This Master is run under the context of Action No 2020-EU-IA-0087, co-financed by the EU CEF Telecom under GA nr. INEA/CEF/ICT/A2020/2267423

Types of deep NN

- Convolutional **Neural Networks** (CNNs);
- Recurrent **Neural Networks** (RNNs);
- Long Short-Term **Memory** Networks (LSTMs);
- Generative Adversarial Networks (GANs);
- Multilayer Perceptrons (MLPs);
- Radial Basis Function Networks (RBFNs);
- Self Organizing Maps (SOMs);
- Deep Belief Networks (DBNs).

This Master is run under the context of Action No 2020-EU-IA-0087, co-financed by the EU CEF Telecom under GA nr. INEA/CEF/ICT/A2020/2267423

Convolutional Neural Networks, CNN

They consist of multiple layers and are mainly used for **image processing and object detection**.

In 1988 Yann LeCun developed the first CNN called **LeNet** for character recognition such as zip codes and numbers.

CNN are used for:

- identification of satellite images;
- medical image processing;
- anomaly detection;
- time series forecasting (a sequence of data measured usually at successive points in time) - for the prediction of future values based on previous observed values.

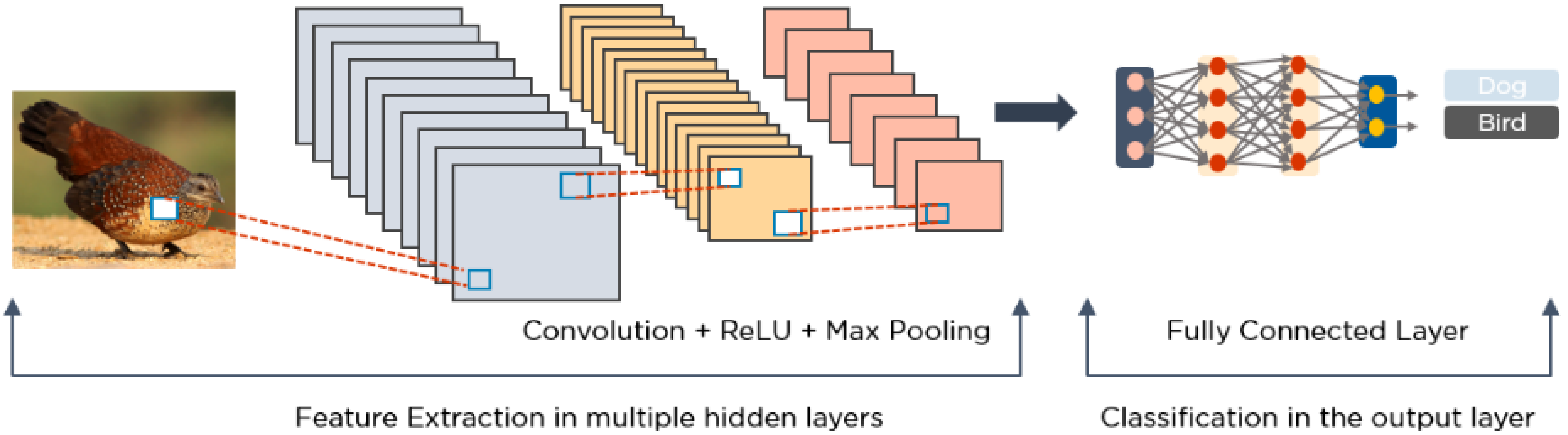
This Master is run under the context of Action No 2020-EU-IA-0087, co-financed by the EU CEF Telecom under GA nr. INEA/CEF/ICT/A2020/2267423

CNN layers

- **Convolutional layer** - there are several filters for performing the convolution operation (in mathematics, convolution is a bias function);
- **Rectified Linear Unit** (ReLU) - a layer for performing operations on elements in order to correct the feature map.
- **Pooling Layer** - reduces the dimensions of the feature map and transforms the resulting 2D arrays of the pooled feature map into a long, continuous, linear vector by flattening it.
- **Fully connected layer** – the linear vector is fed as input which classifies and identifies the images.

This Master is run under the context of Action No 2020-EU-IA-0087, co-financed by the EU CEF Telecom under GA nr. INEA/CEF/ICT/A2020/2267423

Example of an image, processed through CNN



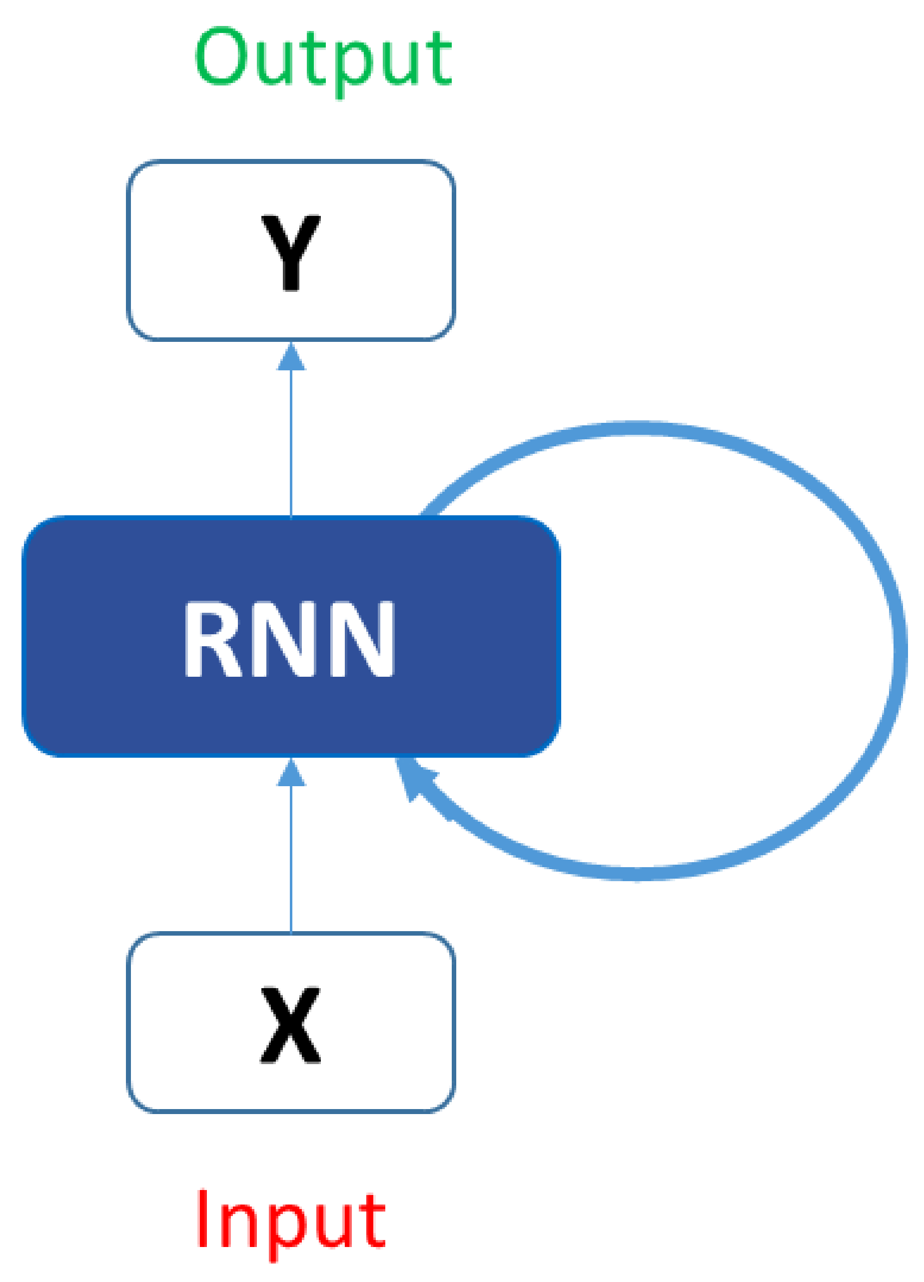
This Master is run under the context of Action
No 2020-EU-IA-0087, co-financed by the EU CEF Telecom
under GA nr. INEA/CEF/ICT/A2020/2267423

Recurrent NN, RNN

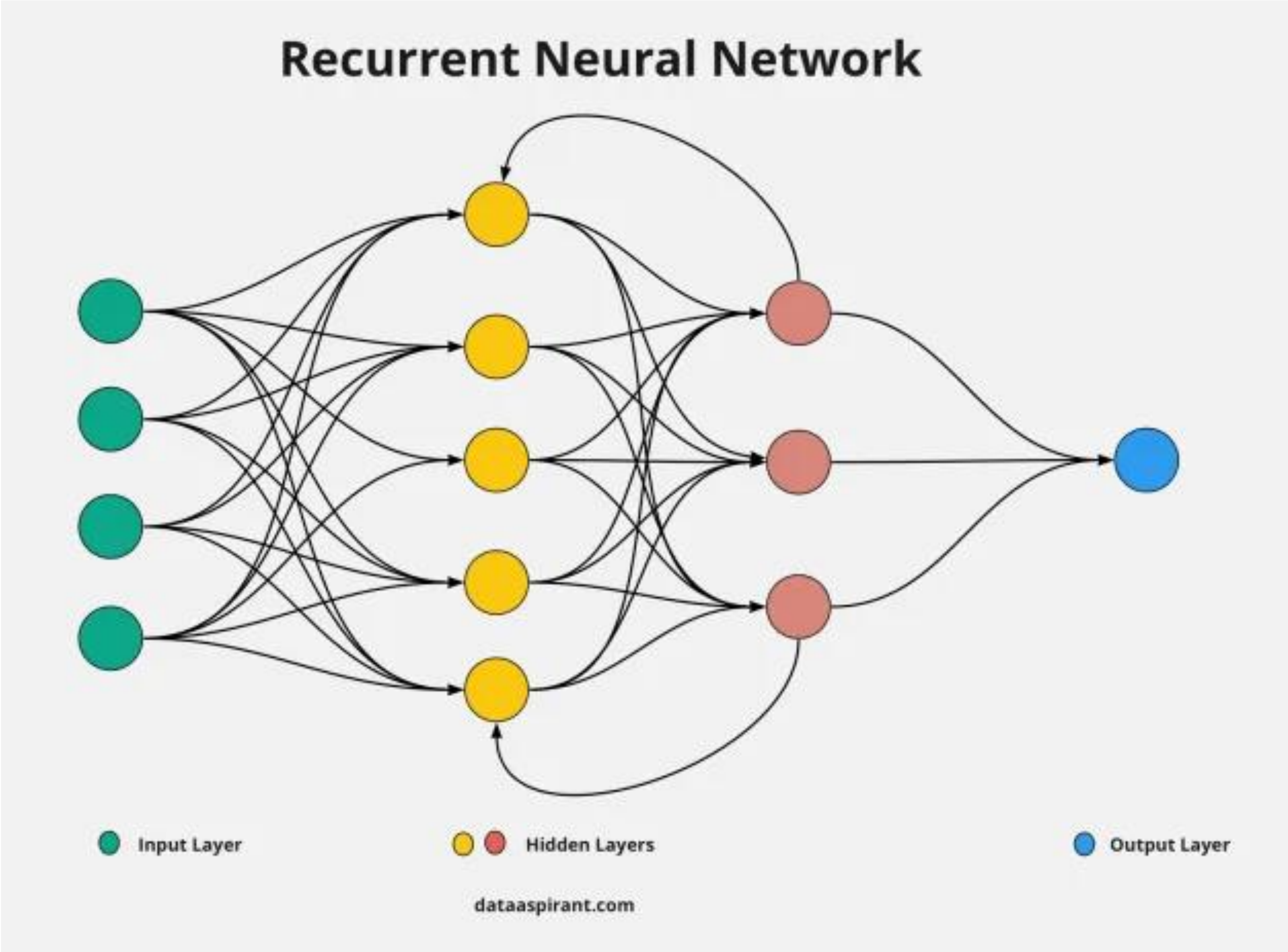
RNNs have connections that form directed loops that allow outputs to be fed as inputs to the current phase. The output becomes the input for the current phase and can remember previous inputs due to its internal memory.

Application:

- image captioning;
- time series analysis;
- natural language processing;
- handwriting recognition;
- machine translation.



Recurrent NN, RNN



RNN limitations

RNN remembers things only for a short period of time i.e. if we need the information after a short time, it can be reproducible, but after many words are entered, this information is lost somewhere.

This problem can be solved by applying a slightly modified version of RNNs – long short-term memory networks.

Co-financed by the European Union
Connecting Europe Facility

This Master is run under the context of Action No 2020-EU-IA-0087, co-financed by the EU CEF Telecom under GA nr. INEA/CEF/ICT/A2020/2267423

Long short-term memory networks, LSTM

A type of recurrent NN that can learn and remember long-term dependencies based on past information over long periods (retains information over time).

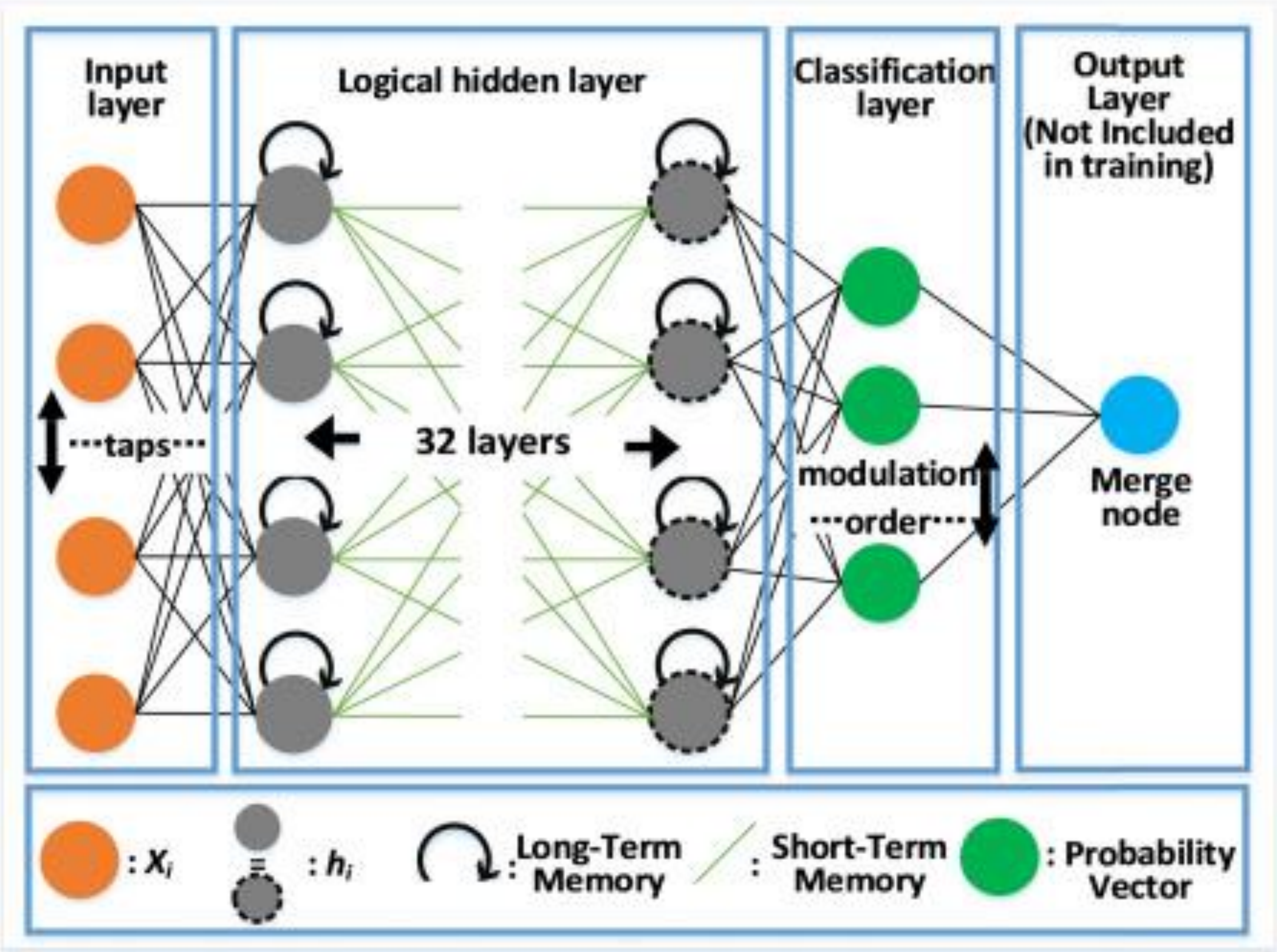
LSTM has a chain-like structure of 4 interacting layers.

Application:

- in time series forecasting;
- for speech recognition;
- for music composition;
- for pharmaceutical development.

This Master is run under the context of Action No 2020-EU-IA-0087, co-financed by the EU CEF Telecom under GA nr. INEA/CEF/ICT/A2020/2267423

Long short-term memory networks, LSTM



Co-financed by the European Union
Connecting Europe Facility

This Master is run under the context of Action No 2020-EU-IA-0087, co-financed by the EU CEF Telecom under GA nr. INEA/CEF/ICT/A2020/2267423

Generative adversarial networks, GAN

GANs are generative deep learning algorithms that create new instances of data that resemble the training data.

GAN has two components:

- a generator that learns to generate fake data;
- a discriminator that learns from this false information.

Application:

- to improve astronomical imaging and simulate gravitational lensing to study dark matter.
- to upscale low-resolution 2D textures in old video games by having programmers recreate them at higher resolutions through image training.
- to generate realistic images and cartoon characters by creating photographs of human faces and rendering 3D objects.

Co-financed by the European Union
Connecting Europe Facility

This Master is run under the context of Action No 2020-EU-IA-0087, co-financed by the EU CEF Telecom under GA nr. INEA/CEF/ICT/A2020/2267423

Multilayer perceptron, MLP

MLPs belong to the NN class of feedforward multi-layer perceptrons that have activation functions. They have no backlinks.

It is a feedforward network whose goal is to approximate some function f *.

Example: a classifier function y = f * (x) converts an input x to a category y. The feedforward network defines y = f (x; θ) and learns the value of the parameters θ, that lead to the best approximation of the function.

Co-financed by the European Union
Connecting Europe Facility

This Master is run under the context of Action No 2020-EU-IA-0087, co-financed by the EU CEF Telecom under GA nr. INEA/CEF/ICT/A2020/2267423

Multilayer perceptron, MLP

Application:

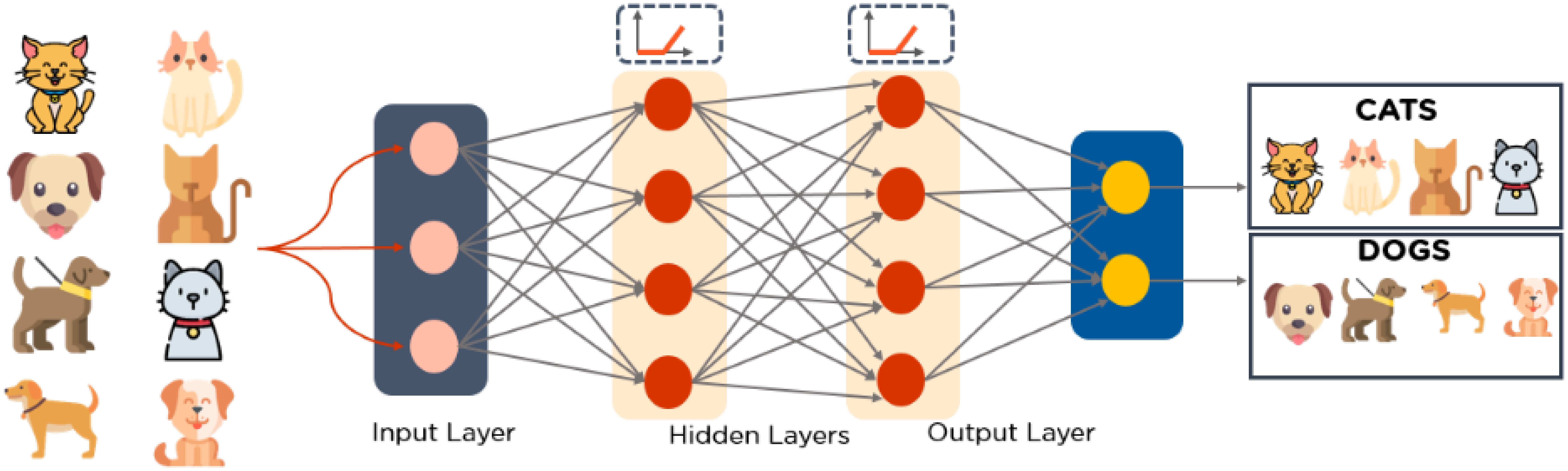
- for speech recognition;
- for image recognition;
- for machine translation.

When feedforward NNs are extended to include feedback loops, they are called **recurrent neural networks**.

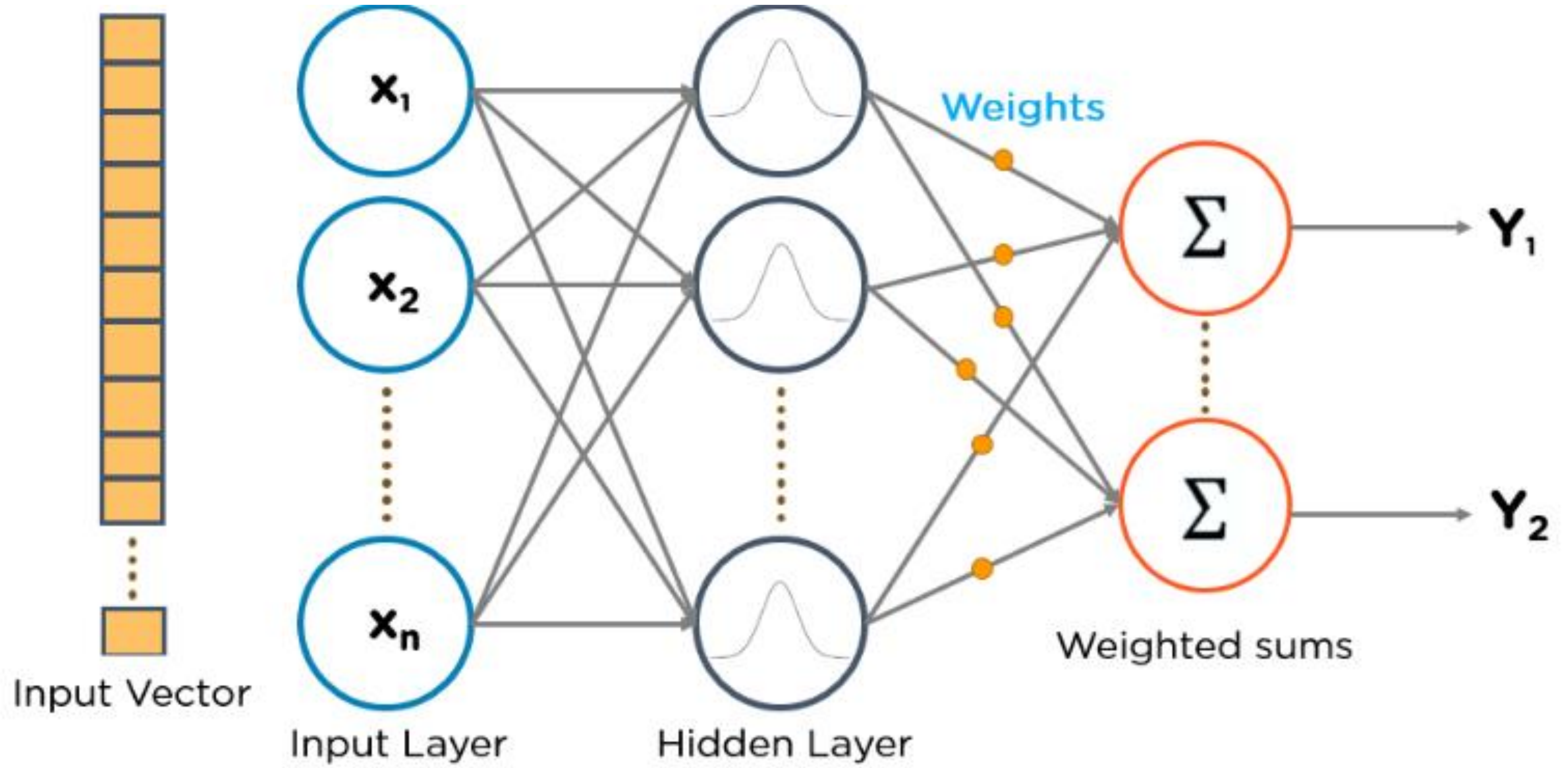
Co-financed by the European Union
Connecting Europe Facility

This Master is run under the context of Action
No 2020-EU-IA-0087, co-financed by the EU CEF Telecom
under GA nr. INEA/CEF/ICT/A2020/2267423

An example of MLP for classifying cat and dog images



Feedforward network architecture



Universal approximation theorem

Hornik and Cybenko, 1989.

A feedforward network with a linear output layer and at least 1 hidden layer, with any activation function (e.g. sigmoid) can approximate any measurable Borel function (French mathematician: For any function f $\in$ C[a,b] and for any non-negative number n there exists an nth-degree polynomial for best uniform approximation of f) from one finite measurable space to another with any desired non-zero amount of errors, given that the network is provided with enough hidden units.

I.e. there is a network, large enough to achieve the desired degree of accuracy, but the theorem does not say how large that network would be.

Co-financed by the European Union
Connecting Europe Facility

This Master is run under the context of Action
No 2020-EU-IA-0087, co-financed by the EU CEF Telecom
under GA nr. INEA/CEF/ICT/A2020/2267423

MAI4CAREU

Master programmes in Artificial Intelligence 4 Careers in Europe

Co-financed by the European Union
Connecting Europe Facility

This Master is run under the context of Action No 2020-EU-IA-0087, co-financed by the EU CEF Telecom under GA nr. INEA/CEF/ICT/A2020/2267423