Chapter 1

Introduction

1.1 Motivation

Artificial neural networks (ANN) are biologically inspired computing systems.

ANN differ from conventional computing systems. Usually, in conventional programming, a definite program is written to solve a specific task. ANN in contrast can learn to solve a task, i.e., given task-related data they generate a sort of program that solves the task, may change the program with new data and can generalise to cases not yet encountered. In this sense, ANN are more flexible, adaptive and general than conventional computing systems.

The modern deep learning (DL) models build on ANN but are usually more complex and may introduce novel elements and ideas.

ANN & DL have many roots; inter alia in neuroscience and computer science. The relation between them is twofold: On the one hand, understanding how biological or neural systems work can help to discover and design novel algorithms. This is because the brain and neurons work very differently from conventional computation. Brains perform poor in tasks where the computer excels e.g. in arithmetics. For example, computing something simple like $31 \cdot 64 = 1984$ takes the brain a long time compared with the computer. However, brains are extremely good at difficult tasks like vision where conventional computers struggle. Thus it is expected that a better understanding of neurons and neural networks may lead to the development of novel algorithms and machines. This may allow to solve practical problems yet not solvable. On the other hand, the brain and its functions are difficult to study as we deal with a very complicated and living system. Therefore theoretical models and computer simulations are used to advance its understanding.

The theory and applications of ANN & DL lies at the intersection of many fields: computer science, computational neuroscience, cognitive science, artificial intelligence, software engineering, mathematics and physics. The general field incorporating neural network learning is called the field of artificial intelligence (AI), see Figure 1.1. Artificial intelligence aims to build "intelligent" machines.

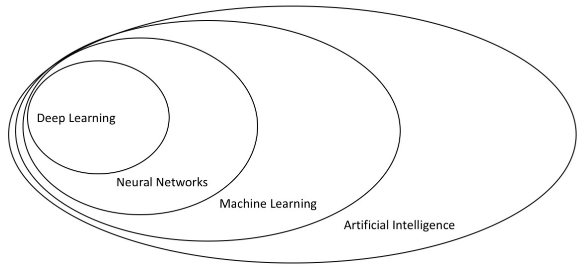

Figure 1.1: The field of artificial neural networks in relation to other fields.

This involves many technical, conceptual and philosophical issues which cannot be addressed in depth in this course. In any case, most researchers view the development of learning systems as a crucial step towards "artificial intelligence".

The study of intelligence and artificial intelligence has a long history. More specifically, in the field of ANN there were several waves of research activity. The latest was triggered by the recent advent of "deep learning". These days the research field is thriving. Since ca 2010 there is an accelerating transition to applications and businesses. The big "tech companies" employ large teams dedicated to AI research and to AI applications and also many start-ups venture into AI related fields.

1.2 Biological Foundations

Let us first look at the biological foundations from which the field of artificial neural networks has drawn inspiration.

The basic computational unit in animals is the neuronal cell called neuron. A neuron is a specialized cell for communication and computation. There are different types of neurons but the typical neuron has the following components: a cell body called soma, dendrites and an axon, see Figure 1.2. From the cell body, at the axon hillock, the axon reaches out to other neurons. The point of contact with the dendrites is called a synapse. The dendrites usually branch multiple times, reaching out to other neurons, thereby receiving inputs from other neurons.

Roughly, neurons function as follows:

1. At the axon hillock synaptic inputs, so-called postsynaptic potentials, are summed and once a triggering threshold is exceeded, an action potential is generated.

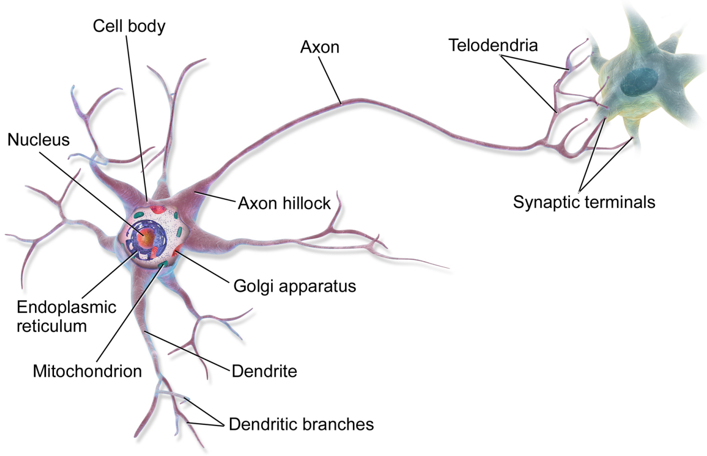

Figure 1.2: Schematic view of a neuron. From Wikimedia Commons.

2. The action potential propagates as an electrochemical wave along the axon.

3. When the action potentials reaches the synapse, a neurotransmitter is released thereby passing a chemical signal to the dendrites or soma of another neuron. Sometimes the signals are also passed electrically.

4. Postsynaptically, the chemical (electrical) signal causes an excitatory or inhibitory membrane potential. The excitatory potential make the postsynaptic neuron more likely to fire an action potential while an inhibitory potential makes a neuron less likely to generate an action potential.

It is believed that the synapse plays a crucial role in regard to memory: As a result of the signaling mechanism, the connection between two neurons is strengthened when both neurons are active at the same time. The strength of the connections is then associated with the storage of information, i.e., memory.

There exist various neuron models that aim to describe mathematically the functioning of biological neurons. One of the simplest models is the Integrate-and-fire model [1]: information processing is conceived as a summation process ("integration") with a mechanism that triggers, above some critical value, an action potential. The Hodgkin-Huxley model [11] was the first mathematical model that described in more detail how action potentials in neurons are initiated and propagated. Lately, the models by Rulkov [24] and Izhikevich [12] have been shown to be able to reproduce spiking and bursting behaviour of the known types of cortical neurons.

At which level of description a neuron is modelled depends on the kind of problem one is studying or the task to be solved and the computational resources. In artificial neural networks applications simplified artificial neurons are used that mimic only certain aspects of their biological counterparts.

Interconnected biological neurons form a biological neural network. The brain contains a huge number of neurons: It is estimated that the human brain contains around 86 billion neurons and 16 billion neurons in the cerebral cortex, the area believed to host most cognitive actions. In comparison, the number of stars in the milky way is estimated to be 200-400 billion. Interestingly, primates possess around 30 billion neurons and elephants even 250 billion neurons and some whales and dolphins even have around 32 billion neurons in the cortex, which is double the number of neurons in the human cortex. Each human neuron has on average around 1000 synaptic connections to other neurons. Thus, there are around $10^{14} = 100$ trillion connections in the brain. In comparison, the observable universe is estimated to hold around 10^{23} stars.

Networks of artificial neurons (ANN) are partly inspired by their biological counterparts. Compared to the biological systems, very simple neuron models, network architecture, etc. are usually used in ANN. Nevertheless ANN & DL models excel in a wide range of tasks as we will see in the course of this lecture.

1.3 What is Learning?

In contrast to conventional computing procedures artificial neural networks do not follow a specific written program to solve a task. Instead they learn how to solve a task. Learning in neural networks is loosely based on insights from learning in biological neural networks and in cognitive science. There are three main learning types:

- Supervised learning
- Unsupervised learning
- Reinforcement learning

Supervised learning can be thought of as learning with a “teacher” that gives feedback to the network. Specifically, the network learns from labelled data, that is, to each input example there is a desired output example called target. During training the network learns to output the target by comparing its output with the target via a cost function. There exist various cost functions depending on the task at hand. The overall aim is to generalise to unseen cases, that is, to correctly determine the output for unseen instances. Typically, supervised learning is used for classification or pattern recognition tasks and for regression or function approximation tasks.

In unsupervised learning, the network learns without a “teacher”, that is, there is no feedback to the network that says whether its output is correct. The main goal of unsupervised learning is to find a good low- or high-dimensional representation of the input. Such a representation can then be used for subsequent supervised or reinforcement learning. Another major aim is to find clusters or patterns in the data.

In reinforcement learning, the network learns how to take actions in some environment in order to maximise some sort of reward. In contrast to supervised learning the correct input/output pairs are thus not presented to the network. When some action is performed the environment generates some observation data and some reward in form of a cost function, according to some (usually unknown) dynamics. The rewards may be delayed and sometimes even missing. The aim is then to discover a series of actions that minimises some measure of long-term cost.

1.4 When Do We Need Neural Network Learning?

Often real-world problems are very complex and may not easily be describable in mathematical form. If they are describable mathematically the ensuing equations may not be solvable or it may be computationally expensive to do so. Also, it is often not clear what kind of underlying process generates the data encountered in real-world situations.

However, we know that there exist biological systems that can “solve” problems that are hard for conventional computing machines. For example, it is easy for us to recognise familiar faces whereas this task is hard for conventional algorithms. It is hard to write a specific program solving this task because we do not know how exactly the brain does it. Also the conditions, in facial recognition e.g. the lighting conditions, may vary a lot and may never be exactly the same. Also it is usually the case that we are presented with new faces that should be added to memory and the algorithm should be able to do so also. Neural network learning aims to close this gap between the cognitive faculties of animals and conventional programming. Indeed, it may even be the case that neural networks attain superhuman capabilities in certain tasks.

The neural network approach is to collect data, e.g. in the case of supervised learning, to collect lots of examples that show the correct output for a given input. The neural network learning algorithm then takes these examples, learns to reproduce them and to generalise to new examples. This produces effectively a “program” that solves the task. The program may change whenever new data is available. In contrast to conventional software, the resulting program may not be easily interpretable, i.e., it might be the case that is hard to understand how exactly the program manages to solve a task.

Nowadays neural network theory and applications is a thriving research field and has many industrial applications. In the course of the on-going “digitalization” of the business world, artificial intelligence technologies are being applied in all kinds of business fields. It is very likely that this process further accelerates.

In order to hint at the wide application field, we list here some of the main applications of ANN & DL. Note that it is not possible to give a conclusive overview of all the application cases of ANN & DL technologies.

- Object recognition and labeling: Convolutional neural networks are successfully used in **object recognition** and **object labelling**. Object recognition is the problem of finding and identifying objects in an image or video sequence. Object labelling is the problem to label objects in an image or video sequence.

- Speech recognition: deep feedforward neural network and recurrent neural networks are widely used in **speech recognition task**, i.e., the automated recognition and translation of spoken language text.

- Natural language processing: Generally, neural network technologies are heavily used in the problem field of processing large natural language data. This involves tasks such as **machine translation**, **chatbots**, **semantic extraction**.

- Recommender systems: a **recommender system** makes recommendations to an user, e.g. to items the user might be interested in. Convolutional and recurrent neural networks have been used by various researchers and companies, e.g. for music recommendation. Note that also e.g. Google's search algorithm is a kind of recommendation system.

- In **online learning** the data is only available in a sequential or temporal order. This might be the case because training over the whole dataset is infeasible or because the data is generated sequentially. For example, a recommendation system is set up to adapt to certain user patterns which are dynamically changing in time. For this type of learning, shallow neural networks are often successfully used.

- Reinforcement learning has been successfully used in **video games**, both for generating them as well as playing them. Such systems nowadays perform better than the human counterparts in **board games** such as chess and go.

- Reinforcement learning models are also heavily used in **robotics** and **self-autonomous driving**.

- **Generative models** such as generative adversarial networks (GANs) can produce high-quality data such as images.

- Supervised and unsupervised ANN are successfully used in **data analytics** such as feature extracting tasks or pattern analysis. ANN may even be developed as a **self-programming technology**, that is, as networks that can learn to code simple programs from examples of desired behaviour.

Note again that we list here only a few examples of well-known application fields. The field is rapidly developing, both in academics and in industry, and there seems at the moment no limit to potential application cases.

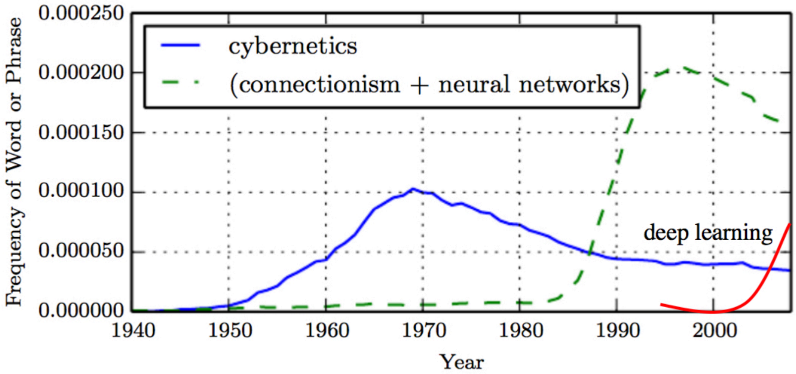

Figure 1.3: Historical waves of artificial neural nets research, measured by the frequency of the phrases "cybernetic" and "connectionism" or "neural networks", according to Google Books [7].

1.5 History

The idea of building intelligent machines, studying the functioning of the human mind and brain, has a long scientific and philosophical history going back to ancient thinkers.

In the context of the current field of machine learning and artificial neural network theory, there have been three main developments: cybernetics in the 1940s-1960s, connectionism starting in the 1980s and the recent trend in deep learning, see Figure 1.3.

Roughly, the milestones in the field are:

1943 The McCulloch-Pitts neuron developed by Warren McCulloch and Frank Pitts was an early model of a neuron, that is, the first artificial neuron model [17]. The work demonstrated that Boolean logic can be encoded by a neural network.

1948 The work of Norbert Wiener, especially his book *Cybernetics: Or Control and Communication in the Animal and the Machine* [29] and the work of his co-workers is considered to be the beginning of modern artificial intelligence research.

1953 The perceptron invented by Frank Rosenblatt [22, 23] was the first neuron model that could learn to solve a task by updating its weights according to input-output examples. The perceptron also lead to the probably first hardware implementation of a neural network.

1960 The ADALINE neural network by Widrow and Hoff [28] is an evolution of the perceptron that can learn by gradient descent.

1969 The book *Perceptrons* by Minsky and Papert [19] discussed critically the perceptron concept and is perceived to have led to a decline in ANN research. The ensuing time is called the "first AI winter".

1980s Development of the Neocognitron by Fukushima [6], a hierarchical multi-layer ANN, that inspired convolutional neural networks.

1990s Kernel machines and graphical models lead to a further decline in neural networks research. The "second AI winter" was there.

1997 Long short-term memory (LSTM) network presented by Hochreiter and Schmidhuber [10], a recurrent neural network that later found many applications especially in natural language processing tasks.

1990s/2000s Development of convolutional neural networks by LeCun et al. [15] and others which found many applications especially in vision processing tasks.

2006/7 Deep learning (DL) "officially" starts with Hinton, Bengio, LeCun [14] and others.

2010s DL takes off: many breakthrough applications lead to a DL and AI hype. Media, businesses and politics speculate on an "AI revolution".

2020s Your time!

1.6 Disclaimer and Literature

These lecture notes were devised and written for the course "Artificial Neural Networks & Deep Learning" in the Master's programme Applied Computational Life Sciences at the University of Applied Sciences (ZHAW). The lecture notes are intended only for internal use and shall not be distributed.

These lecture notes are partly based on the book by Hertz, Krogh and Palmer [8], the lectures notes by Hinton et al. [9], the book by Goodfellow, Bengio and Courville [7], the book by Chollet [3] and research articles mentioned in the text.

The theory and application of ANN & DL is a very active field with many online sources on theory, applications and software codes. Go find out yourself!