

**Bilingual End-to-End Deep Learning**

**Speech Recognition System**

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# **ABSTRACT**

“a **summary** of the report (100-200 words), which should fully encapsulate the content of the project, being informative, interesting and for appropriate aspects, quantitative” (General Guidance)

**Further Information**

Read Learning Centre tip sheet: Writing up the report: Writing an Abstract

**Example**

Birmingham based registered youth charity St Basils’ required an Information System (IS) that could be used as an interesting medium for communicating relevant resident information on the World Wide Web. Rapid Application Development (RAD) Methodology – Throwaway Prototyping, Computer Aided Software Engineering (CASE) tools helped to develop this system at a fast rate and to accomplish the project in the short time scale given. With the design stage of the Systems Development Life Cycle (SDLC) complete, a flexible, powerful yet easy to use server-side scripting language was required. PHP was chosen as it fulfilled the previous criteria. To complement PHP, MySQL database server was chosen to store the relevant data for the website, because of the speed at which PHP and MySQL are able to interact. A highly accessible web site was created to meet the charity’s needs.

# **ACKNOWLEDGEMENTS**

“identifying those from whom assistance has been received.” (General Guidance)

**Example One**

I would like to thank all the staff from the Centre for Academic Success, Brian Fanning at CA Associates, Sasha Johnson, John Kempson, and Kate Chandler. I should also like to thank: Julie, Tracy, Maria, Meredith, Charlie, Kaz, Geoff Phillips, Ian Urguhart, Kit Wallace, Luke Brennan, Garry Lunn, Richard Cliff, Mum, Dad, Ginnie and everyone else who helped.

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# **GLOSSARY**

“of symbols and abbreviations” (General Guidance)

When creating the glossary it is best to insert a table and then remove the borders. This will make the glossary look neatly organised.

**Example One**

|  |  |
| --- | --- |
| SDLC | Systems Development Lifecycle |
| RAD | Rapid Application Development |
| SAD | Systems Analysis and Design |
| SQL | Structured Query Language |
| XML | Extensive Markup Language |

**Example Two**

|  |  |
| --- | --- |
| BAO | Body Assembly Operations |
| CAL | Customer Acceptance Line |
| FTPM | Ford Total Productive Maintenance |
| OTA | Off Track Area |
| RR | Rolling Road |

# **LIST OF DIAGRAMS AND TABLES**

When creating the List of Figures and Tables it is best to insert a table and then remove the borders. This makes the Lists look neatly organised. Word features (references tab) can also be used to automatically maintain such lists.

**Example**

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# **INTRODUCTION**

Speech recognition is the technology that allows a computer of any kind to capture human speech in the form of a sound wave and convert it into written text. Also known as Automatic Speech Recognition (ASR) or Speech-to-Text (STT), this technology can have various sets of characteristics that depend on the purpose and needs that the system is built to serve. For example, such systems can be large-vocabulary for general purpose speech recognition or small-vocabulary for a specific application where only a certain set of commands is being used. Also, they can be speaker-dependent or speaker-independent based on whether the system was intended to be used respectively by a single user or by the wider public.

Despite being one of the most natural and simple functionalities in people, ASR has always been a task of high complexity for a computer, due to the unpredictability and variance of speech. As a result of many years of extensive research and experimentation, numerous different approaches to ASR exist, some of which will be explored and discussed in greater detail in the following chapters.

## **Problem Definition**

For many years the development of functional speech recognition systems relied on specialized knowledge of the language of interest and all of its specifics, requiring the recruitment of linguists and other specialists to build accurate acoustic and language models. All grammatical rules, pronunciation specifics, etc. had to be hardcoded in the system, which was time consuming, made those systems large in size, therefore impractical to incorporate in mobile applications, and inflexible to different pronunciations and dialects and unusable on another language.

In 2014, Alex Graves and his team introduce the innovative idea of end-to-end speech recognition deep learning model which would automatically learn the pronunciation and acoustic models and would remove the need for specialized language knowledge and hand modelling, given enough training examples (Graves et al., 2014). Shortly after that, Baidu Labs created the Deep Speech (1 & 2) system to build on Graves’ idea and prove that an ASR system can be trained to recognize two different languages with little or no changes in the system (Amodei et al., 2016).

This project will explore the essence of end-to-end speech recognition and will take the idea of Deep Speech further to demonstrate that a single deep learning model can be trained to recognize and transcribe both English and Bulgarian language, regardless of the significant differences in the two languages, including the use of different alphabets (Latin and Cyrillic).

## **Scope**

Over the provided seven-month period for the completion of this project, three main stages can be identified – research of the existing technologies, design of the proposed model and implementation and evaluation of the system.

In the research stage, the project briefly reviews the history and advancement of speech recognition, evaluates the strengths and weaknesses of each approach and justifies the choice of the end-to-end approach to ASR. At this stage, an overview of the basics of machine learning and its relevant areas is presented as well.

The relevant sections to the design stage present a proposed architecture for a large-vocabulary, speaker independent deep learning model which has the ability to convert both English and Bulgarian speech into text. All of the model’s components and their functionality are described in details.

The sections on the implementation and evaluation proceed to present the process of implementing of the system, including the hardware and software tools and resources used for the completion of the project. All testing scenarios and results are laid out and a critical discussion of the project results and limitations is carried out.

Finally, a short conclusion summarises the key findings and proposes possible further improvements to the system.

## **Rationale**

With the rapid evolution of smart technologies nowadays and specifically the AI and IoT, which are seen as two of the focus areas of development in what is called The Fourth Industrial Revolution, the demand for more advanced and accurate speech recognition algorithms and systems is growing exponentially.

For people with various severe physical impairments, speech recognition is a new opportunity for easier and better communication and interaction with the modern world.

The choice of this topic was motivated by the creation of Baidu’s Deep Speech 2 system as well as the increasing interest and necessity for speech recognition systems in the modern society. Nowadays, technology takes an increasingly big part of people’s everyday lives and communicating efficiently with it is crucial.

## **Aims**

The overall aim of this project is to develop and implement a bilingual end-to-end deep learning ASR system, based on Baidu’s Deep Speech 2 system, which will work in English and Bulgarian.

## **Objectives**

* Research the history and fundamentals of speech recognition.
* Examine and contrast all existing algorithms and methods for achieving speech recognition and justify the final choice of approach.
* Design a model architecture for the ASR system. based on Baidu’s Deep Speech 2 system. (🡨 should I add the text in red to the sentence?)
* Obtain speech corpora in both languages for training and testing.
* Formulate a methodology and develop a suitable application based on the available resources.
* Test the system with different configurations and sets of hyper-parameters and evaluate the label error rate and efficiency of the designed system.
* Critically evaluate the results and project limitations and propose further improvements.
* Develop a web application for easy and straightforward user interaction with the system. (if I have time; I’ve worked a lot with node.js, html and css, so that shouldn’t take long if I have a few spare days)

## **Background Information**

Should I add any information about the cyrillic alphabet and Bulgarian language here and maybe explain the major differences from English or should I this section as a whole? Background knowledge on the history of speech recognition is included in Review of Existing Knowledge (next section).

# **REVIEW OF EXISTING KNOWLEDGE**

## **Speech Recognition – History and Importance**

Automatic speech recognition has been an area of interest since the 1950s. Initially, researchers were exploiting the acoustic-phonetic features characterising speech sounds. The first attempt for creating an ASR system was made in Bell Laboratories in 1952 by Davis, Biddulph and Balashek. They created an isolated digit recognizer that operated by analysing the spectral content in the vowel region of each digit in order to detect specific spectral resonances (Davis et al, 1952).

By the mid-1970s, the new basic concept of pattern recognition was introduced. It was based on the newly developed methods for spectral analysis – Linear Predictive Coding (Itakura and Saito, 1970; Atal and Hanauer, 1971).

In the 80’s, template-based pattern recognition, which in its essence did not incorporate any automatic learning, was quickly replaced by the newer concept of the statistical-based, probabilistic modelling. In the following three decades, most ASR systems were relying mainly on Hidden Markov Models (HMM) combined with Gaussian Mixture Models (GMM). During that time, the concept of artificial neural networks (ANN) was already introduced and used in many systems (Waibel et al., 1989; Bourlard and Wellekens, 1989; Bengio et al., 1991, 1992; Robinson and Fallside, 1991; Konig et al., 1996). However, it did not gain much popularity among researchers, due to its performance being similar to the one of HMM-GMM models, and were only used for separate small tasks inside the HMM-GMM model.

Over the years, researchers slowly started gaining more interest in deep learning models after their successful implementation in numerous applications and once the performance of GMM-HMM models reached a plateau regardless of the growing data sets, the focus of researchers quickly shifted onto deep learning (Goodfellow et al., 2017).

Over the years, researchers have overcome many limitations like speech segmentation, temporal non-uniformity, background noise, etc. However, ASR still faces various imperfections and therefore remains a research topic of high interest. The following section will explore the evolution of deep learning for speech recognition over the years in greater depth through critical analysis of the existing research.

* 1. **Critical Review of Previous Research**

Baker (2009) states that arguably the most important advancement in the historical progress of speech recognition systems was the introduction of stochastic processing with HMMs as part of the acoustic model in the new for the time statistical approach to ASR that deals with the temporal variability of speech (Baker, J. K., 1975; Jelinek, F., 1976). *Figure 1* shows a high level representation of the typical statistical speech recognition system. With the introduction of the expectation maximization (EM) algorithm (Dempster et al., 1977), training HMMs for real-world speech recognition applications became possible. The EM algorithm uses GMMs to form a probabilistic representation of the relationship between acoustic input and the HMM as a mixture of Gaussian probability distributions.

However, Hinton et al. (2012) explain that despite the many advantages of GMMs, they are statistically inefficient when it comes to modeling data that lies close to or on a nonlinear manifold in the data space. He argues that the underlying structure of speech has lower dimensionality than initially observed in a window with numerous coefficients. Models with the ability to exploit embedded information of lower dimensionality in a big window of frames would operate more efficiently on such data. When trained discriminatively by backpropagating error derivatives, artificial neural networks (specifically feed-forward deep neural networks) can process such manifold data much more efficiently, given enough computational power. In their paper, Hinton and researchers from four prestigious organizations explain and demonstrate a two-stage procedure for training a DNN for acoustic modeling. They tested both the GMM and the DNN training procedures on six different large-vocabulary tasks (hours of training data ranging from 24 to 5870) and found the DNN-HMM model’s performance to be equal to or exceeding the one of highly tuned GMM-HMM even in cases where the latter is trained with much more data.

The major conclusion from their study is that applying purely generative pretraining as a the first stage would prevent overfitting and speed up the discriminative fine-tuning process later by training each feature detection layer based on its preceding layer using Deep belief networks (DBN), instead of designing all feature detectors at once and by hand. The DBN would initialize weight values that are close to the good global solution and the discriminative process of back-propagation through the DNN would only need to adjust the weights very slightly (Mohamed et al., 2011; Mohamed et al. 2012).

In the second stage of fine tuning, however, DNNs have the disadvantage of lacking the ability to use parallelism, which can slow down the process as data sets grow larger.

Even though different kinds of neural networks have replaced many key components of the typical complex ASR system (*see Fig. 1*) over the years, some of the base components have remained the same for decades and most of the existing systems are HMM-based. In traditional speech recognition systems, features are extracted from the raw input acoustic waveform and a neural network is trained to classify frames of this acoustic data, the output distributions of which are then transformed into emission probabilities for the HMM. Such systems also have to include a language and a pronunciation model, specifically designed for the language of interest, in order to predict an output sequence.

In their paper, Graves and Jaitly (2014) propose a new and simplified end-to-end approach to speech recognition systems that directly transcribes audio data with little or no hand-engineered language and pronunciation modelling, removing the necessity for an intermediate phonetic representation. They argue that existing HMM-based ASR systems require significant human expertise and complex modeling which can often slow down the development and training process and could be avoided by this end-to-end approach.

Despite the fact that end-to-end speech recognition can be achieved without any preprocessing of the raw input waveform (Graves, 2012), it proved to significantly decrease the system’s performance and add to the computational cost of the model. Graves and Jaitly (2014), therefore, decided to use spectral audio representation as a minimal preprocessing. Their proposed system combines a deep bi-directional Long short-term memory (LSTM) recurrent neural network (RNN), which processes the spectrograms, with a Connectionist Temporal Classification (CTC) output layer which deals with aligning input data to text transcripts of different sizes and training the RNN model. Decoding is performed with a beam search algorithm. To improve the decoding speed and efficiency, Miao et al. (2015) suggest embedding individual decoding components (language models, lexicons and CTC labels) into weighted finite-state transducers.

The findings of this study show that the proposed system works successfully even in the absence of a language model, provided it is trained with a large data set. However, using simple language models helps reducing the word error rate (WER) even further. Using a trigram language model brings the WER down to 8.2% from the original 27.3% obtained from training without any prior linguistic information (Graves and Jaitly, 2014).

Maas et al. (2015) suggest a further improvement to Graves and Jaitly’s system by performing character-level decoding of the RNN outputs as opposed to word-level ones, which give the system the ability to transcribe new words and fully eliminates the need for a lexicon.

In their paper, explaining Deep Speech – a similar end-to-end speech recognition system, Hannun et al. (2014) outline that traditional speech recognition systems tend to show poor performance in noisy and non-isolated environments, unless they incorporate specifically designed components to model such interferences. An end-to-end deep learning system, on the other hand, can learn and adjust itself to effects like reverberation, background noise or speaker variations without the need for such components, given that a large labeled training set, which includes enough examples with the above-mentioned effects, is provided. While it is possible to collect and label large amounts of data containing the distortions of interest, it is extremely inefficient in practice and it can take incomprehensible amounts of time and resources. As an alternative, Hannun et al. suggest generating the necessary data by modifying the existing “clean” data set. This process, also called superposition of the source signals, consists of adding a noise track to the original signal  in order to simulate audio captured in a noisy environment without having to physically record it. Further processing can be applied as well like adding echoes, reverberations, delay or other effects that need to be handled by the system.



It is important to note, however, that for synthesizing noisy speech tracks from *n* hours of clean recordings, roughly *n* hours of non-repetitive noise recordings will be necessary as well. If the noise track is repeating numerous times over the training set, there is a risk for the RNN to memorize it and subtract it out of the newly synthesised track. For the purpose, Hannun suggests collecting and using many shorter audio clips, which can be easily extracted from public video sources, instead of sourcing an *n*-hour long one.

The results from the Deep Speech system showed a great improvement in noisy speech recognition, compared to various popular systems with 19.06% WER on noisy speech as opposed to 43.76% WER for Apple Dictation. For a combination of noisy and clean speech, the Deep Speech system performed with only 11.85% WER, compared to 26.73% for Apple Dictation. This proves that superposition of the training signals as a means for generating noisy speech to add to the training set leads to significantly better performance of the system, compared to hand-engineering those distortions in the sound.

Amodei et al. (2016) take the idea of the end-to-end deep learning approach further by developing Deep Speech 2 in order to demonstrate how such a system can recognize two entirely different languages with little or no expert knowledge on any of the languages. The architecture of this system resembles the one of the original Deep Speech – 20ms windows of spectral content serves as an input for a recurrent neural network, having 1-3 convolutional input layers and a number of uni/bi-directional layers, followed by a fully connected and a softmax layer (consisting of the alphabet of the respective language). The end-to-end training is achieved by using the CTC loss function. The CTC model is combined with a language model and beam search is used for estimating the most probable transcription.

However, for the RNN units Amodei et al. use gated recurrent units (GRUs) instead of LSTMs. Introduced in 2014 (Cho et al.), GRUs have the same concept as LSTMs. However, GRUs have a simpler structure with less parameters and do not include a memory cell, which makes them much faster to train (Chung et al., 2014).

To further improve the performance of the system, Amodei et al. apply batch normalization throughout the whole network and SortaGrad to the training set – a technique for classifying minibatches of training examples in terms of difficulty, which is determined by the length of the longest utterance in a minibatch.

Like in (Hannun et al., 2014), the training set is a combination of collected data and an augmented version of it with added noise and effects. The results of the training show a 40% relative decrease in WER for each factor of ten increase in the size of the training set.

From the results it can be concluded that 2D convolutional layers provide a significant improvement in the WER for noisy data, as opposed to 1D layers that provide only a small benefit both for the clean and the noisy data. The transition from a single 1D to three 2D convolutional layers showed improvement of 23.9% in the WER on noisy data.

The adaptation to Mandarin required minimal changes, all depending on the Chinese character set. Instead of outputting probabilities for 29 characters (letters a-z, space, apostrophe, blank), the network outputs probabilities for 6000 characters. Then a character level language model is used, since Mandarin is not segmented by words in text. Similarly, the system that recognizes Bulgarian language will output probabilities for 32 characters (30 letters from the Cyrillic alphabet, space, blank). Either word or character level language model can be used, based on availability.

An innovative alternative for sequence-to-sequence encoding-decoding to CTC was introduced recently, called attention mechanism. First applied in the fields of machine translation (Bahdanau et al., 2015), visual object classification (Mnih et al., 2014), image caption generation (Xu et al., 2015), etc., the attention mechanism was later applied to speech recognition as well (Chorowski et al., 2015). It provides the output sequence generator in a network the ability to access any part of the input sequence, instead of a compressed version of the whole input in the form of a single vector. Thus, the model can focus its attention to a specific part of the input signal based on a set of weights associated with each element of the input sequence.

In their work on an end-to-end attention-based LVSCR system, Bahdanau, et al. (2016) use an Attention-based Recurrent Sequence Generator (ARSG) as a decoder network. The ARSG outputs a sequence of elements (*y1,…, yt*) generated from the sequence (*h1,…,hn*), which is just the encoded representation of the input signal *x*. The ARSG is composed of an RNN and an attention mechanism which selects specific locations from the input sequence and use them to update the hidden state of the neural network based on their attention weights and to estimate the following output value.

The results from this experiment (Bahdanau et al, 2016) show that attention-based systems perform better than CTC systems in the absence of an external language model with 18.6% WER for ARSG compared to 35.8% WER for a CTC system (Hannun et al., 2014). However, when an external language model is used, CTC systems still outperform attention-based ones. In the presence of an extended trigram language model, the ARSG system produces 9.3% WER while a CTC system produces 7.3% WER (Miao et al., 2015). Therefore, the choice of model type should be made based on the language model availability.

In the past few years, most of the research in this field has been centered around the idea of end-to-end systems. Many researchers keep developing the attention-based approach (Toshniwal et al., 2017; Kim and Seltzer, 2017), others still work with CTC systems (Liptchinsky et al., 2017; Zeghidour et al., 2018) and there are a few research teams looking into hybrid CTC/attention-based systems (Hori et al., 2018) . This project will aim for the implementation of the CTC approach, similar to the one proposed by Amodei et al. (2016) due to its established success and the wide range of existing research on the topic.

The following section will provide a brief overview of the base theory behind machine learning, necessary for the understanding of deep learning systems.

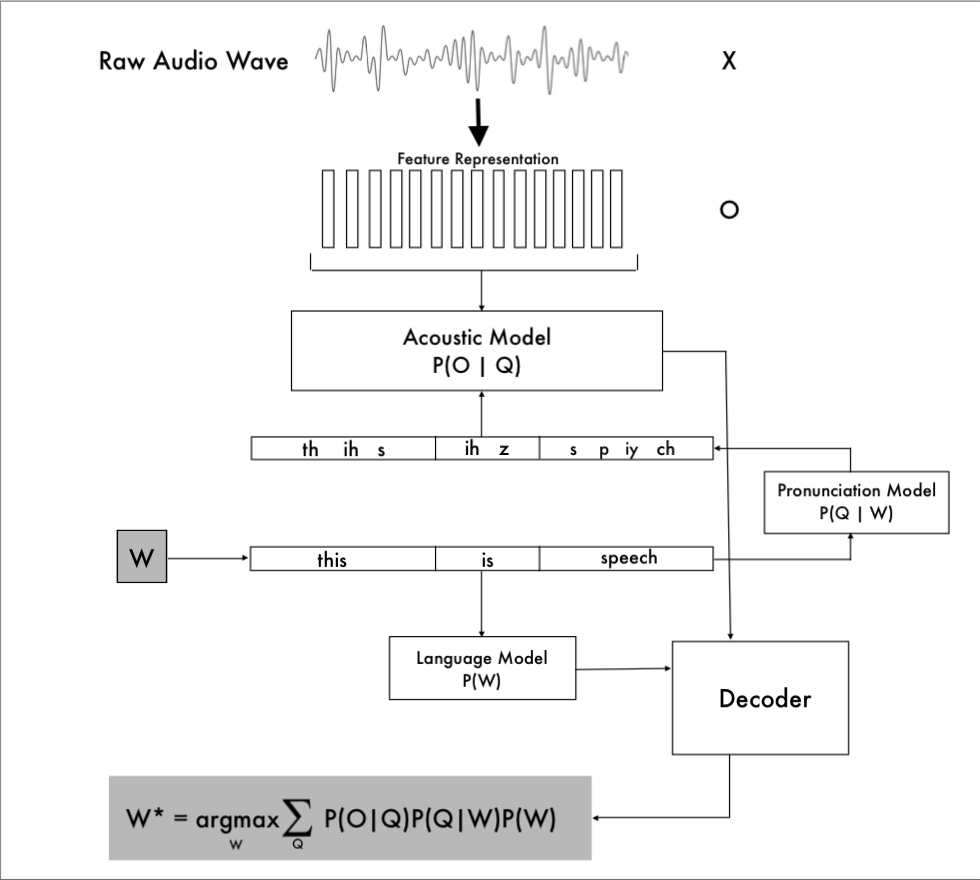


Figure 1: A high level statistical speech recognition system diagram, showing the computation of the maximum value of the probability P(W|X) of word sequence W given the acoustic input X. The diagram was composed based on a similar one provided by Steve Young (1996) in ‘Large Vocabulary Continuous Speech Recognition: a Review’ and the lecture slides from Adam Coates’ Speech recognition and Deep Learning presentation in Stanford.

* 1. **Machine Learning**
     1. **Basics**

Machine learning is a subfield of artificial intelligence that aims to replace the explicit programming of a system with automatic acquisition of knowledge based on a given set of data or as Mitchell (1997) describes it, it is the improvement in performance P with experience E on a task T.

Depending on the type of the training data set, the following 3 main types of machine learning algorithms can be identified:

* **Supervised Learning Algorithms**

An algorithm is considered supervised when all examples from the training data set are associated with their respective expected outputs, also called label. Given the vector *x* and its associated vector *y*, the algorithm attempts to learn how to predict unknown values for *y* from a given *x* by estimating the conditional probability distribution p(*y* | *x*) by using maximum likelihood estimation. Linear regression is considered the simplest supervised learning algorithm.

* **Unsupervised Learning Algorithms**

An algorithm is considered unsupervised when the training set contains elements with many features, but no labels associated. The model is expected to identify common patterns and useful properties in the structure of the training data, without having any expected output values. In other words, the algorithm attempts to determine the probability distribution p(***x***) or a distinctive property of it given a random vector *x*.

The k-means clustering is a popular unsupervised learning algorithm, which divides the training data set into a number of clusters of similar data points (MacQueen, 1967).

* **Representation algorithms**

A representation algorithm is not given a fixed data set to work with. Instead, it experiences an interaction with its environment and receives a feedback after each of its actions as a form of a reward. The purpose of a representation algorithm is to learn to perform in way that will maximize the total rewards signal over a certain amount of iterations (Sutton and Barto, 1998).

* + 1. **Neural Networks**
       1. **Artificial Neural Networks**

An ANN is simply a network of nodes structured in layers – usually an input layer, one or more hidden layers and an output layer. Each hidden layer consists of units that perform nonlinear operations to the input signal:

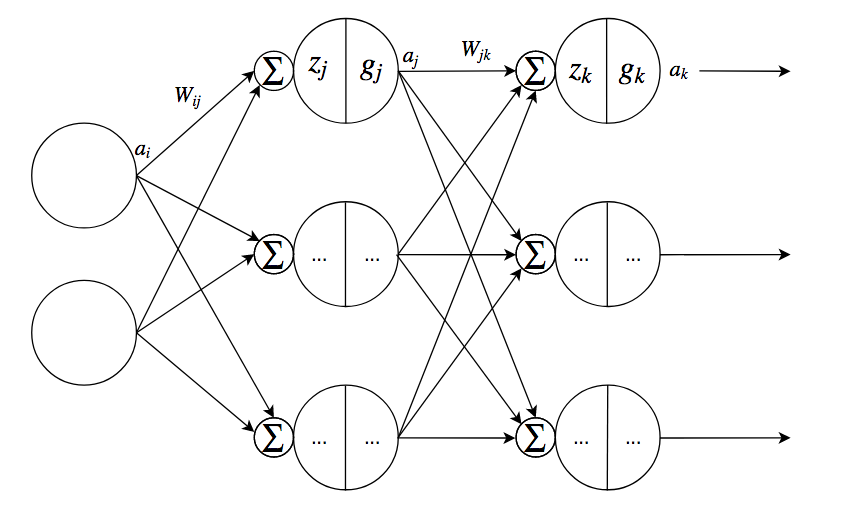


Figure 2: A generic artificial neural network structure.

where

In a generic feed-forward artificial neural network, the following calculations can be observed:

1. The input signal *ai* for each node in the input layer is multiplied by a weight matrix *Wij* which connects the input layer with the hidden layer.
2. Those products are then summed and a bias value is added. This operation forms the input of each node of the hidden layer *zj* .
3. The input of each hidden node is then multiplied by the layer’s nonlinear activation function *gj* to produce the output of the layer - *aj* .
4. Similar to the previous steps, the output of each hidden node is multiplied by the weight matrix *Wjk* , a bias *bk* is added and the signals are summed to produce the input of the output node – *zk* .
5. *Zk* is then multiplied by its activation function *gk* to produce the neural network’s output values *ak..*

Artificial neural networks are used for modelling very complex relationships in data that occur in tasks like image labelling, handwriting recognition or speech recognition. They achieve this by constantly updating their internal parameters in order to fit to the input data.

A deep neural network is simply an artificial neural network with multiple hidden layers. There is no formal definition for the number of layers beyond which a neural network is considered deep.

* + - 1. **Recurrent Neural Networks**

Recurrent neural networks are a subset of neural networks that have at least one recurrent connection in their hidden layers, meaning that each hidden node takes as inputs not only the current input value (*xt*), but also the value of the hidden node for the previous time step (*ht-1*) in order to produce an output value (*see Eq. 1 & Fig. 3*).

|  |  |  |
| --- | --- | --- |
|  |  | (1) |

where *U* and *W* are the respective weight matrices and *b* is the bias matrix.

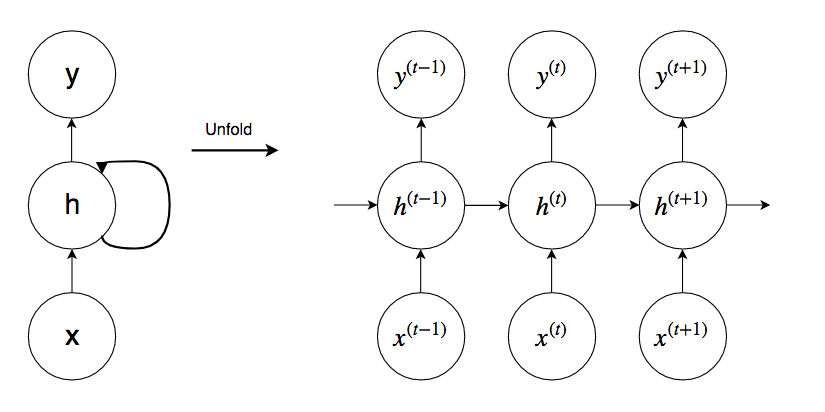


Figure 3: A generic recurrent neural network structure with one hidden layer.

* + - 1. **Convolutional Neural Networks**

Convolutional neural networks are a special type of ANN which is used for processing data with grid-like structure. Their main objective is to extract high-level features from given data (most widely used for image processing). As the name indicates, CNNs make use of the linear mathematical operation called convolution (add info in appendix), as opposed to the general matrix multiplication used in regular ANNs. A kernel (i.e. a small window of values) of certain size is being convolved with different sections of the input structure to produce an element of the output matrix. CNN makes use of the so called weight sharing, meaning that the same set of weight values (in the kernel) are used for all sections of the input, thus preventing overfitting and reducing the number of weights to learn, which contributes to the model’s robustness (Abdel-Hamid et al., 2014; *see Fig. 4*).

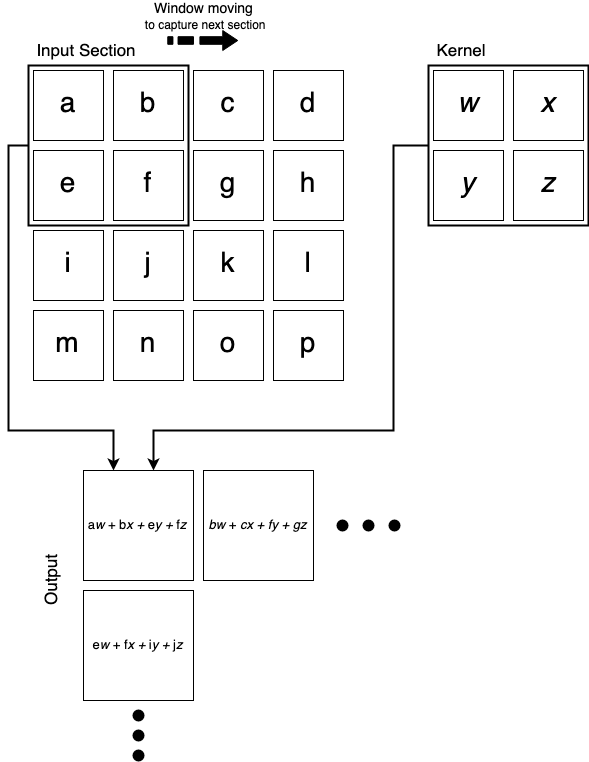


Figure 4: A generic example of 2-D convolution with no padding and kernel of shape [2, 2].

If no padding is added to the inputs, such networks reduce the dimensionality of the input data structure.