**CHAPTER 6**

**NEURAL NETWORKS**

This chapter is dedicated to description of NN in general and its special type called CNN.

**6.1 History**

History of Neural networks can be arguably dated from 1943, when Warren Mcculloch and Walter Pitts invented mathematical model encouraged by the Biology of central nervous systems of mammals [25].

This encouraged the invention of Perceptron, created in 1958 by Frank Rosenblatt. Perceptron used very modest model mimicking biological neuron that was based on the mathematical model of Pitts and Mcculloch. Definition of the Perceptron model also defined an algorithm for direct learning from data.

In the beginning Perceptron looked very promising, but it was soon discovered that it had severe restrictions. Most projecting voices of criticism were Marvin Minsky. Minsky published book in which he laid out a case that the Perceptron model was unable to resolve complex problems [26]. Amongst others the book contained mathematical proof that Perceptron is incapable to solve simple XOR problem. More generally the Perceptron is only proficient of solving linearly separable problems. However, according to Minsky, this criticism wasn’t malicious, it in effect stifled the interest in NNs for over a period.

Awareness in NNs was rejuvenated in the early 80’s, when it was shown that any previously raised up deficiencies could have been resolved by usage of multiple units. This was later exacerbated by development of back-propagation learning algorithm, which allowed the possibility to gather neurons into groups called layers, which can be weighted into hierarchical structures to form a network. NN of this type were generally called Multilayer Perceptron (MLP). In 80s and 90s the awareness in NNs plateaued again and general research on AI was more focused on other machine learning methods. In the field of classification problems, it was particularly SVM and ensemble model. AI research communities also established several other paradigms of NNs that were likewise inspired by Biology of certain aspect of central nervous system but took different methods. Most significant examples were SOM and Recurrent Neural Network (RNN).

By the year 2000, there were very few research groups that were applying enough attention to the NNs. There was also certain disdain for NNs in the academic world and AI research community. The success of NNs that was promised almost half a century ago was finally coming across around 2009, when the first networks with huge number of hidden layers were effectively trained. This led to typical adaptation of umbrella term deep learning which by and large refers to Deep Neural Network (DNN). The term deep indicates that networks have a large number of hidden layers

The key theoretic vision was to learn complex functions that could represent high-level abstractions such as vision recognition, language understanding, etc. There is a requirement for deep architecture.

NNs in the times before Deep Neural Networks had only one or two hidden layers. These are currently called shallow networks. Typical Deep Networks can have a number of hidden layers in order of 10’s, but in some cases even hundreds [18]

Still progress of Neural Network into the direction of structures with high number of hidden layers was obvious, its training was an unresolved technical problem for a very long time. There were fundamentally three reasons why this invention didn’t come sooner

1. There were no procedure allowing the number of hidden layers to measure.

2. There wasn’t enough of labeled data required to train the NN.

3. The computer hardware wasn’t powerful enough to train adequately large and complex networks successfully.

The first problem was tackled by the creation of CNNs [24]. The second problem was explained simply when there were more data presented. This was primarily achieved thanks to effort by large companies like YouTube, Google, Facebook, etc. But also with support of large community of experts and hobbyists in data sciences.

Both inventions in computational hardware and improvement of training methods were needed to resolve the third problem. One of the technical revolutions was use of Graphics Processing Units (GPUs) for the demanding computation involved in the training of a complex network. Thanks to the fact that training process of NNs is typically large number of simple resulting computations, there is a great possibility for parallelization.

**6.2 Structure of Neural Networks**

The term NN is very general and it defines a comprehensive family of models. In this framework NN is distributed and parallel model that is capable of approximating complex nonlinear functions. Network is made from multiple computational components called neurons assembled topology.

Explanation of NN structure will follow the convention laid out in the explanation of learning algorithm. Meaning that an explanation of the learning algorithm is composed of model, cost function and optimization technique. The difference comes into performance with the fact that the model of NN is much more complex than the model linear regression. Therefore, the investigation is divided into model of neuron and topology of the network.

**6.2.1 Model of Neuron**

Neuron is computational unit carrying out nonlinear transformation of its inputs

𝑦 = 𝑔(𝑤𝑇𝑥 + 𝑏). (6.1)

Argument 𝑤𝑇𝑥 + 𝑏 of function 𝑔 is often observed as 𝑧. Therefore, the equation can be rewritten as

𝑦 = 𝑔(𝑧). (6.2)

Typical schema is shown on Figure 6.1, which describes inputs, weights bias and activation function.



Figure 6.1: Diagram of artificial neuron [29].

As it was already stated model of neuron was stimulated by biology. First attempts to make a model of a neuron had multiple elements equivalent with neurons of the human brain. As research proceeded this equality ceased being as important and modern NN models correspond to their biological matching part only superficially.

**Inputs**

Each neuron has multiple inputs 𝑥 that are combined to execute some operation. Each input has elected weight assigned to it.

**Weights**

Inputs of a neuron are weighted by parameters 𝑤 that are changed during the learning process. Each weight gives strength to each individual input into the neuron. The basic awareness is that when the weight is small the input doesn’t affect the output of the neuron very much. Its effect is large in the opposite case.

**Bias**

Another changeable parameter is bias 𝑏 that controls impact of the neuron as a whole.

**Activation Function**

For NN to estimated nonlinear function each neuron must perform the nonlinear transformation of its input. This is completed with activation function 𝑔 (𝑧) that performs the nonlinear transformation. There are numerous different normally used activation functions. Its usage depends on the type of network and on the type layer in which they activate.

One of the oldest and historically most frequently used activation functions if sigmoid function. It is defined by

𝑔(𝑧) = 1 1 + 𝑒 −𝑧 . (6.3)

Problem with sigmoid is that its gradient becomes flat on both extremes and as such it reduces the learning process [23].

One more activation function is hyperbolic tangent. It is defined as

𝑔(𝑧) = 𝑡𝑎𝑛ℎ(−𝑧). (3.4)

Hyperbolic tangent function is not use that much in feed forward NN, but it is mostly used in RNN. Currently most commonly used activation function is Restricted Linear Unit (ReLU). It is very generally used in both convolutional and fully connected layers. It is defined by

𝑔(𝑧) = max{0, 𝑧}. (3.5)

It has a disadvantage because it is not differentiable for 𝑧 = 0, but it is not a problem in software execution and one of its biggest advantages is that it can learn very speedily.

All three activation functions are illustrated in Figure 3.2.

**6.2.2 Topology of the Network**

There are several different generally used topologies. The two most frequently used in deep learning are feed-forward and recurrent. Feed forward networks are categorized by the fact that during activation the information move only in a forward direction from inputs to outputs. A recurrent network has some sort of feedback loop.

Another principle of topology is how are individual neurons in the network linked. Most commonly are NNs ordered in layers. In each layer there can be from one to n neurons. Layers are hierarchically fixed.  The first layer is called input layer, the last layer is called an output layer and the layers intermediate are called hidden.

Description of the network recreations on interconnections between individual layers. The most common structure is called fully connected where to each neuron in hidden layer 𝑙 has input associates from all neurons from previous layer 𝑙 − 1 and its output is associated with input of each neuron in following 𝑙 + 1 layer. The entire structure is illustrated in Figure 6.3.



Figure 6.2: Activation Functions

After this point on the term NN will refer to Feed-forward Fully Connected Neural Network.

Types of neurons are dependent on the type of the layer. Currently the core difference is in their activation function, which wasn’t the case for a long time. In history all layers had neurons with sigmoid activation function. It was mostly because the output sigmoid layer can be easily mapped onto probability distribution, since it obtains values between 0 and 1. Only relatively recently it was found that network composed of neurons with ReLU activation function in the hidden layers can be trained very speedily and are more resistant against over-fitting. Activation functions are still subject of ongoing research.

Neurons in output layer necessity output that can produce probability distribution



Figure 6.3: Fully connected Feed Forward Neural Network [21].

that can be used for approximation the probability of individual classes. For this reason, most frequently used activation function of output neuron is called SoftMax.

SoftMax is standardized exponential function. It is used to represent probability of an instance existence member of class 𝑗 as

𝑔(𝑧)𝑗 = 𝑒 𝑧𝑗 ∑︀𝑘=1 𝐾 𝑒 𝑧𝑘 , (3.6)

where 𝐾 is total number of classes.

**6.2.3 Cost Function**

Cost functions of NNs are a complex subject that exceeds the scope of this thesis. One of the most common cost functions used in NNs for classification in multiple classes is categorical cross entropy. For SoftMax activation function from Equation 6.6 is a cost function defined as

𝐶 = − 1 𝑛 ∑︁𝑛 𝑖=1 𝑦 (𝑖) ln 𝑔(𝑧 (𝑖) ) + (1 − 𝑦 (𝑖) ) ln(1 − 𝑔(𝑧 (𝑖) )), (3.7)

where 𝑦 (𝑖) if correct class of the instance and 𝑛 is total number of instances.

**6.2.4 Optimization Procedure**

Every optimization technique for NN is constructed on gradient descent. In other words, it is an iterative process that goes to lower training error of the network by differentiating of the cost function and adjusting parameters 𝜃 of the model by following the negative gradient.

The problem is that cost function of the whole network is very complex and has many parameters. To find the gradient of the cost function, it is compulsory to go through all the units in the network and estimate their contribution to the overall error. A method that is used to solve this problem is called back-propagation.

Back-propagation if frequently confused to be a complete learning algorithm which is not the case, it is only the method to compute the gradient [16].

**Back-propagation**

To approximation the influence of individual units in a network the back-propagation is used to compute delta 𝛿 𝑙 𝑗 , where 𝑙 is layer and 𝑗 is index of neuron in that layer. Algorithm starts at the output of NN, more exactly its cost function.

𝛿 𝐿 = ∇𝑥𝐶 ⊙ 𝑔 ′ (𝑧 𝐿 ) (6.8)

where 𝐿 is last layer of the network and ∇𝑥𝐶 is gradient of cost function with respect to 𝑥 and ⊙ is the Hadamard product.

In subsequent lower layers the deltas are calculated as

𝛿 𝑙 = ((𝑤𝑙+1) 𝑇 𝛿 𝑙+1 ⊙ 𝑔 ′ (𝑧 𝑙 ) (6.9)

where (𝑤𝑙+1) 𝑇 is from Equation 6.1.

Each neuron has two changeable parameters 𝑏 and 𝑤. To estimation the rate of change for parameter 𝑏 𝑙 𝑗 from Equation 6.1 it needs to be computed as

𝜕𝐶 𝜕𝑏𝑙 𝑗 = 𝛿 𝑙 𝑗 (6.10)

Change of weight 𝑤 𝑙 𝑗𝑘 from Equation 6.1 it needs to be computed as

𝜕𝐶 𝜕𝑤𝑙 𝑗𝑘 = 𝑥 𝑙−1 𝛿 𝑙 𝑗 (6.11)

**Gradient Descent Optimization**

Back-propagation estimations gradient of all modifiable parameters 𝑏 and 𝑤 in the network. These parameters can be denoted by vector 𝜃. Therefore, the gradient of the function to be minimized can be written as ∇𝜃𝑡−1 𝑓(𝜃𝑡−1).

Modest learning algorithm is called gradient descent. Even though simple, it is very robust learning algorithm.

𝑔𝑡 ← ∇𝜃𝑡−1 𝑓(𝜃𝑡−1) (6.12)

𝜃𝑡 ← 𝜃𝑡−1 − 𝜂𝑔𝑡 (6.13)

Algorithm has meta-parameter 𝜂, which is often called learning rate. It determines how fast are 𝜃 parameters updated. Modest gradient descent has the shortcoming that update of parameters is always closely proportional to change of gradient. This might turn out to be a problem when the gradient change slows down. This process is also often called Stochastic Gradient Descent (SGD). The word stochastic indicates that during training the algorithm is using random choice of instances to train. There are various variations on the gradient descent method. Following explanations are taken from [14].

**Adam**

It is more complex learning algorithm that combines 𝐿2 norm and classical momentum-based optimization. It should converge quicker than classical Gradient Descent.

𝑔𝑡 ← ∇𝜃𝑡−1 𝑓(𝜃𝑡−1) (3.20)

𝑔^𝑡 ← 𝑔𝑡 1 − ∏︀𝑡 𝑖=1 𝜇𝑖 (3.21)

𝑚𝑡 ← 𝜇𝑚𝑡−1 + (1 − 𝜇)𝑔𝑡 (3.22)

𝑚^ 𝑡 ← 𝑚𝑡 1 − ∏︀𝑡 𝑖=1 𝜇𝑖 (3.23)

𝑛𝑡 ← 𝜈𝑛𝑡−1 + (1 − 𝜈)𝑔 2 𝑡 (3.24)

𝑛^𝑡 ← 𝑛𝑡 1 − 𝜈 𝑡 (3.25)

𝑚¯ 𝑡 ← (1 − 𝜇𝑡)𝑔^𝑡 + 𝜇𝑡+1𝑚^ 𝑡 (3.26)

𝜃𝑡 ← 𝜃𝑡−1 − 𝜂 𝑚¯ 𝑡 √ 𝑛𝑡 + 𝜀 (3.27)

**6.3 Convolutional Neural Networks**

CNNs are specialized type of NNs that was initially used in image processing applications. They are arguably most effective models in AI inspired in biology.

Even though they were shown by many different fields, the main design principles were drawn from neuroscience. Since their achievement in image processing, they were also very successfully implemented in nature language and video processing application.

A fore mentioned stimulation in biology was based on scientific work of David Hubel and Torsten Wiesel. Neurophysiologists Hubel and Wisel, studied vision system of mammals from late 1950 for several years. In the research, that might be measured little gruesome for today’s standards, they linked electrodes into brain of anesthetized cat and measured brain response to visual stimuli [19]. They discovered that feedback of neurons in visual cortex was triggered by very narrow line of light shined under specific angle on projection screen for cat to see. They determined that specific neurons from visual cortex are responding only to very specific patterns in input image. Hubel and Wiesel were given the Nobel Prize in Physiology and Medicine in 1981 for their discovery.

In the following text is assumed that convolutional layer is working with rectangular input data (e.g. images). Even though the Convolutional networks can also be also used to classify one-dimensional or three-dimensional input.

**6.3.1 Structure of CNN**

Structure of Convolutional networks is typically made of three different types of layers. Layer could be either Convolutional, Pooling or fully connected. Each type of layer has different protocol for forward and error backward signal propagation.



Figure 6.4: Structure of Convolutional Neural Network [5]

There are no specific protocols on how the structure of individual layers should be organized. However, with exemption of recent development CNNs are typically structured in two parts. First portion, usually called feature extraction, is using groupings of convolutional and pooling layers. Second portion called classification is using fully connected layers. This is shown in Figure 3.4.

**Convolutional layer**

As the name suggests this layer employs convolution procedure. Parameters supply to this layer is simply called input. Convolution process is performed on input with specific filter, which is called kernel. Output of convolution process is typically called feature map.

Input into Convolutional layer can be image or feature map from previous layer. Kernel is typically of rectangular shape and its width can array from 3 to N pixels. Feature map is created by convolution of kernel over each definite element of input. Convolution is defined in more detail in section describing training of CNN.

Depending on the dimensions of kernel and layer’s padding preferences the process of convolution can produce feature map of different size than input. When the size of output should be preserved it is compulsory to employ zero padding on the edges of input. Zero padding in this case must add essential amount of zero elements around the edges of input. This amount is determined by

p =((h−1)/2) (3.28)

where h is width of used kernel. In contrary case the feature map is reduced by the 2p. Decrease of size of the feature map can be in some cases desirable. Zero padding is shown on Figure 6.5.

Drop of feature map can go even further in case of use of stride. Application of stride specifies by how many input points is navigated when moving to neighboring position in each step. When the stride is one, kernel is moved by one on each step and the resulting size of feature map is not affected. Each Convolutional layer is typically configuration of several different kernels. In other words, output of this layer is tensor holding feature map for each used kernel. Each of these is premeditated to underline different features of input image. In the first layers these features are typically edges. next the layer, the more complex features are captured. Each kernel that is used is applied to all inputs of the image to produce one feature map which basically means that neighboring layers are distribution the same weights. This might not be appropriate in some applications and therefore it is possible to use two other types of networks. Locally linked which basically means that applied kernel is of the same size as the input and smooth convolution which means alternation of more than one set of weights on entire input.



Figure 6.5: A zero padded 4x4 matrix [11]

Smooth convolution is interesting because with clever combination with Max Pooling clarified bellow it allows to train specific feature from multiple positions. Each convolutional layer has non-linearity on its output that is sometimes also called the detector phase. This is equal to activation function of NNs. Activation function of CNN is normally ReLU.

**Pooling layer**

This layer typically doesn’t find any learning process, but it is used to dejected sample size of the input. The Principle is that input is divided into multiple not overlapping rectangular elements and units within each element are used to make single unit of output. This reduce the size of output layer while preserving the most important information checked in input layer. In other words, pooling layer wrappings information contained within input. Type of process that is achieved on each element determines a type of pooling layer. This action can be averaging over units within element, selecting maximal value from element or alternatively learned linear combination of units within element. Learned linear combination introduces form of learning into the pooling layer, but it is not very predominant. Selecting of maximal value is record common type of pooling operation and in that case the layer is called Max-Pooling accordingly. Positive outcome of Max-pooling down-sampling is that take out features that are learned in convolution are invariant to small shift of input. Principle of Max-Pooling is shown on Figure 5.6.

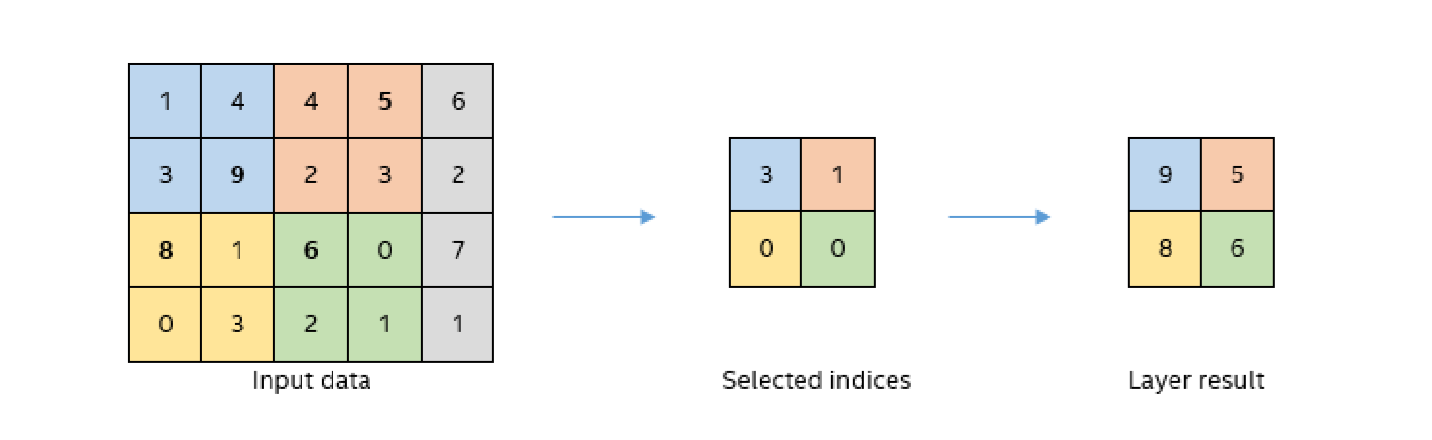


Figure 6.6: Principle of Max-pooling [12]

As already said, another benefit of Max-pooling arises when combined with tiled convolution. To generate simple detector that is invariant to rotation it possible to use four different kernels that are rotated by 90 degrees among each other and when the smooth convolution is used to tile them in groups of four, the Max-pooling makes sure that resulted feature map holds output from the kernel with strongest signal. Max-Pooling layer will be used to define process of training of CNNs.

**Fully-Connected layer**

Fully-Connected layer is equal to layer from Fully Connected Neural Network (FCNN) that was already described. Its training also follows already described procedure.

**6.3.2 Training of CNN**

Optimization procedure of CNN is similarities to FCNN. Situation with CNN is more complex because network is made of different types of layers. Forward signal propagation and backward error propagation are following special protocol for each layer. Calculations used in this section were inspired from [15]. First stage is called forward-propagation, where the signal is broadcast from inputs of the CNNs to its output. In the last layer the output is associated with desired value by cost function and error is estimated. In second stage is again used backpropagation algorithm to estimate error contribution of individual units. Inconstant parameters of the network are again optimization by gradient descent algorithm.

**Forward Propagation of Convolution Layer**

Each convolutional layer is preforming convolution process on its input. Presuming that input of a layer is of length N × N units and kernel is of length m × m. Convolution is calculated over (N−m+1)×(N−m+1) units without zero padding.

Calculation of convolution output xlij is defined as

xlij =m−1 ∑︁ a=0 m−1 ∑︁ b=0 ωabyl−1 (i+a)(j+b) (6.29)

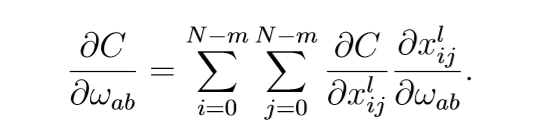
where i,j ∈(0,N −m+1), l is index of current layer, ωab are weights of the kernel and yl−1 (i+a)(j+b) is output of previous layer. Output of convolutional layer ylij is computed by squashing of output of convolution operation xlij through non-linearity:

ylij = g(xlij) (3.30)

where g represents this non-linear function.

**Backward Propagation of Convolution Layer**

Backward propagation for convolutional layer is following the similar principles as described in Section 6.2.4. The difference is in fact that convolution kernel shares weights for entire layer and kernels do not have bias described in Section 6.2.1. Given partial derivative of error from previous layer with respect to output of convolutional layer ∂C ∂ylij, influence of kernel weights on the cost function it needs to calculate



From Equation 6.29 it follows that ∂xlij ∂ωab = yl−1 (i+a)(j+b),thus

∂C ∂ωab =N−m ∑︁ i=0N−m ∑︁ j=0 ∂C ∂xlij yl−1 (i+a)(j+b).

To calculate deltas (equivalent to Equation 6.9) ∂C ∂x (l) ij using

∂x (l) ij using the chain rule

∂C ∂x (l) ij = ∂C ∂ylij ∂ylij ∂xlij = ∂C ∂ylij ∂ ∂xlij(︁g′(︁xlij)︁)︁= ∂C ∂ylij g′(︁xlij)︁

Since ∂C ∂ylij is already given the deltas is calculated by derivation of activation function. Last phase comes to propagation of error into previous layer by equation

∂C ∂yl−1 ij = m−1 ∑︁ a=0 m−1 ∑︁ b=0 ∂ ∂xl (i−a)(j−b) ∂xl (i−a)(j−b) ∂yl−1 ij (3.34)

Again from Equation 6.29 it follows that ∂xl (i−a)(j−b) ∂yl−1 ij

= ωab, therefore

∂C ∂yl−1 ij = m−1 ∑︁ a=0 m−1 ∑︁ b=0 ∂C ∂xl (i−a)(j−b) ωab. (3.35)

The result looks suspiciously like convolution operation and can be taken as convolution of error with flipped kernel.

**Forward Propagation of Pooling layer**

Feed forward operation of pooling layer is strait forward as defined in section 6.3.1. Ratio is typically four to one, which means that input matrix is divided into not overlapping sub-matrices of size 2×2 and each of these produces 1 output. Another possibility is to have overlapping sub-matrices, where length of sub-matrix is larger the number of pixels between application of pooling.

**Backward Propagation of Pooling Layer**

As said in section for forward-propagation, there is no explicit learning process happening in pooling layer. Error is propagated backwards dependent on how the signal was propagated forward. In Max-Pooling layer the error is propagated only to the unit with maximal output in forward-propagation phase. The error is propagated very sparsely, as outcome.

**6.4 Regularization of Neural Networks**

Control of difficulty applies to both NN and CNN. There are several popular regularization techniques that typically consist of adjustment of cost function or optimization algorithm. Somewhat different approach is to modify structure of the network during training stage.

Dropout By far the greatest regularization technique is to combine predictions of many different models. This technique greatly improves generalization ability of combined model while preventing over-fitting. Exactly on this idea are based ensemble models. The problem with ensemble models is that they are required more computational time and very expensive. Because of this, ensembles are usually made of many very simple models [30]. This idea is especially problematic with DNNs, which are model with many parameters that are difficult to train. Moreover, even when trained models are existing in some applications it still isn’t viable to evaluate many different models in production environment. Another problem is that there might not be enough data to train these different models.

All these problems can be resolved by dropout technique. The basic idea is that each neuron in the network has certain probability to be deactivated during one iteration. This potential for deactivation is estimated in every iteration, to ensure that network has different architecture every time. Deactivated means that it will not broadcast any signal through. This forces individual neurons to pick up features that are less dependent on its surrounding.

Possibility for deactivation is a hyper-parameter that can be tuned, but reasonable default value is 0.5. Dropping out is only happening in the training stage. In testing stage are all weight connection multiplied by the probability of a dropout. This is completed because the activation of the network must stay roughly equivalent in both training ant testing stage. Basic concept is shown in Figure 6.7

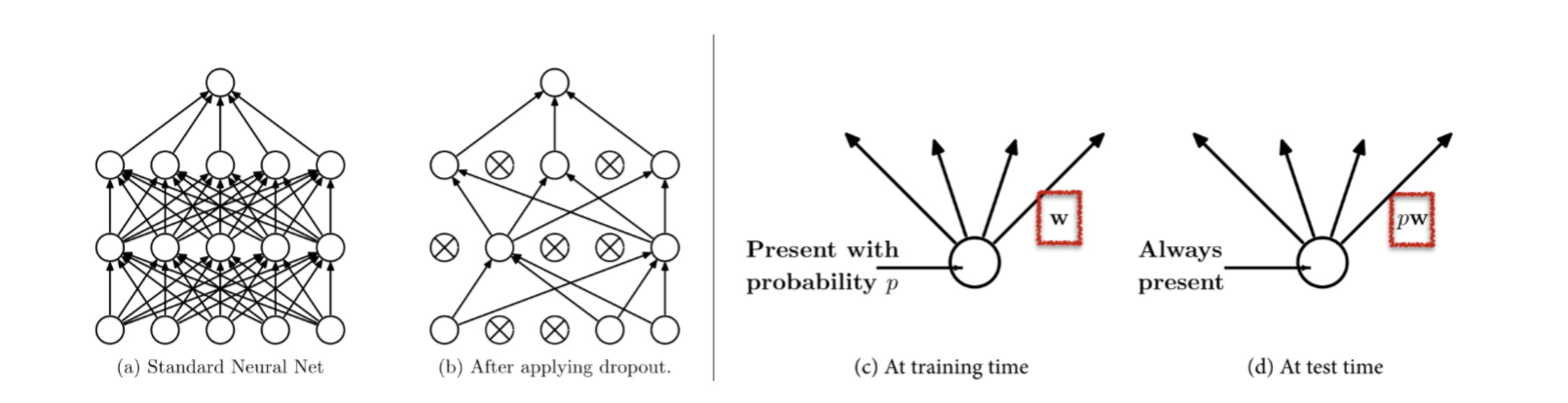


Figure 6.7: Dropout: (a)Standard fully connected network. (b) Network with some neurons deactivated. (c) Activation of neuron during training phase. (d) Activation of neuron during testing phase [4].