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ANALYSIS OF DIFFERENT TYPES OF NEURAL NETWORKS AND THEIR APPLICATION TO REAL-WORLD CHALLENGES

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Abstract: *Nowadays, there has been a great interest around the term "neural network" in the field of computer science. It attracts a lot of attention from many people. In this article, we will look through the most used variations of neural networks, introduce how they work in brief, along with their applications to real-world challenges.*

When we are children, we learn the things with the help we get from the elders. Later by self-learning or practice we keep learning during our whole life. The artificial neural networks are inspired by this processes in the human brain. They learn by detecting patterns in huge amount of information. With the help of neural networks, we can provide solutions of problems for which there is no algorithmic method to be solved with. We don't need to program the neural networks explicitly, they learn how to solve problems by examples.

Neural networks are usually used for statistical analysis and data modelling, in which their role is to serve as an alternative to standard non-linear regression or cluster analysis techniques. That's why, they are typically used in problems that may be formulated in terms of classification, or forecasting. Examples of their use include image (Wang, H., Li, G., Ma, Z., & Li, X., 2012) and speech recognition, textual character recognition (Kalaichelvi, V., Ali, A. S., 2012), forecasting monthly electricity demands (Chen, J. F., Lo, S. K., & Do, Q. H., 2017) and domains of human expertise such as medical diagnosis, geological survey for oil, and financial market indicator prediction.

Keywords: *neural networks, deep learning, artificial intelligence*

INTRODUCTION

Neural networks are a branch of machine learning. They are computational models – essentially algorithms. Neural networks are inspired by the structure of the human brain, once they are trained, they learn on their own. They take input data, train themselves to recognize patterns in the dataset, and then predict the output for a new set of similar data. Neural networks mimics the behavior of the human brain to solve complex data-driven problems. Neurons continually adjust how they react based on stimuli. If something is done correctly, you'll get positive feedback from neurons, which will then become even more likely to trigger in a similar, future instance.

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Conversely, if neurons receive negative feedback, each of them will learn to be less likely to trigger in a future instance.

EXPOSITION

The artificial neural networks (ANNs) are statistical models created to self-program and adapt by using learning algorithms to understand concepts, images and photographs.
The artificial neural network represents interconnected input and output units. Their connections have weights. The weights are adjusting during the learning phase in order to predict the correct class of input data.

There are two kinds of learning: supervised and unsupervised learning. The supervised learning includes labeled datasets, telling the computer what the right answer is, like which emails are spams and which are not. Linear Regression and k-nearest neighbors algorithm (k-NN) are used for such supervised regression or classification. Other datasets might not be labeled, and you are literally telling the algorithm such as K-Means to associate or cluster patterns that it finds without any answer sheet. This is called unsupervised learning.

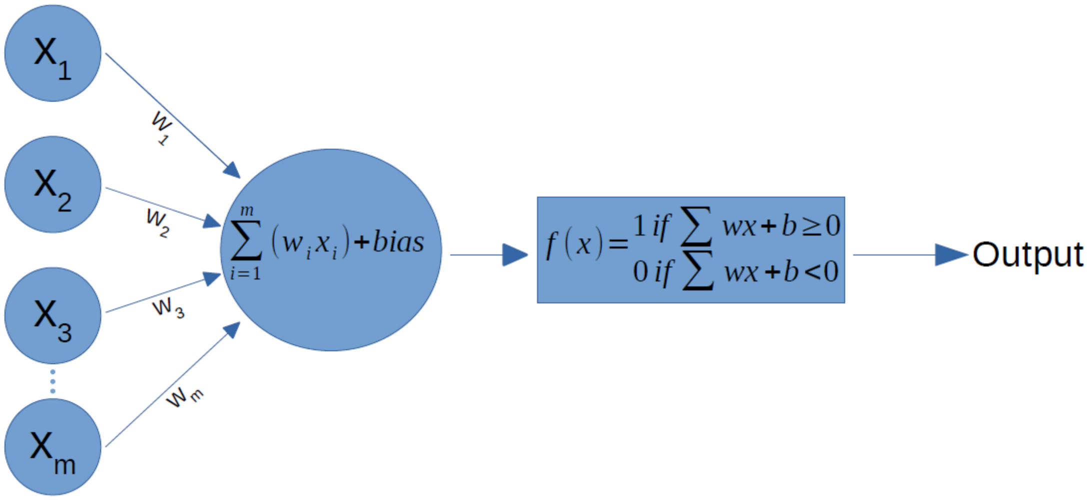

Fig. 1. Perceptron

Figure 1 shows a graph of perceptron. Perceptrons and other neural networks are inspired by real neurons in our brain. The procedure of a perceptron processing data is explained below:

1. On the left, there are neurons (small circles) of x with subscripts 1, 2, …, m carrying data input.

2. Then each of the inputs is multiplied by a weight w, also labeled with subscripts 1, 2, …, m, along the arrow (called a synapse) to the big circle in the middle.

3. Then all of the results from the multiplications are summed. A number called bias is added to this sum.

4. If the result is equal or larger than 0, then we get 1 as output, otherwise we get 0 as output.

If we move bias to the right side of the equation in the function, it will be like$\sum(\boldsymbol{wx}) \geq -\boldsymbol{b}$. This -b is called a threshold value. This ways of representation are interchangeable.

Varying the weights and threshold will result in different possible decision-making models.

The input data and the bias are set before the training of the neural network, so during the training process the perceptron can only adjust its weights. The training process is adjusting the weights until the predictions of the perceptron are equal to the desired results.

This algorithm was invented in 1958 and it is the basis of the neural networks. Neural networks have come a long way since then. They find application at many fields now from simple classification problems to diagnosing cancer better than the physicians.

In this paper, we will analyze three of the most popular types of neural networks: autoencoders, convolutional neural networks (CNNs), and recurrent neural networks.

Autoencoders approach is based on the observation that random initialization is a bad idea and that better initial weights can be allowed by pre-training each layer with an unsupervised learning algorithm. Deep Belief Networks are examples of such unsupervised algorithms. There are a few recent research attempts, for instance, using variational methods for probabilistic autoencoders, to revive this field.

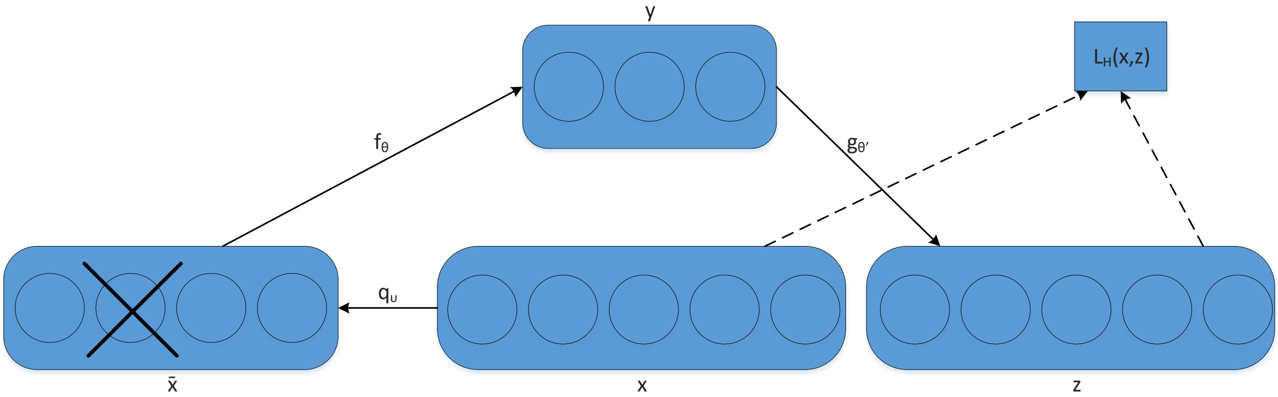

Fig. 2. Denoising autoencoder

In practical applications, they are infrequently used. Recently, batch normalization has begun to allow even deeper networks to be trained. We could train arbitrarily deep networks from scratch using residual learning. With appropriate dimensionality and sparsity constraints, autoencoders can learn data projections that are more interesting than PCA or other fundamental techniques. Two interesting applications of autoencoders are:

- *Data denoising*

For efficient denoising of medical images, a denoising autoencoder (Fig. 2) built using convolutional layers is used. A stochastic corruption process randomly sets some of the inputs to zero, forcing the denoising autoencoder to predict missing (corrupted) values for randomly selected subsets of missing patterns.

- *Dimensionality reduction for data visualization*

It uses techniques like Principle Component Analysis (PCA) and t-Distributed Stochastic Neighbor Embedding (t-SNE) to attempt dimensional reduction. They have been used to improve model prediction accuracy in combination with neural network training. MLP neural network prediction accuracy also is heavily dependent on the design of the neural network, data pre-processing, and the type of problem for which the network was designed.

The convolutional neural networks derive their name from the “convolution” operator, they are a class of deep neural networks, most commonly applied to analyzing visual imagery. The primary reason of using convolution in the case of a convolutional neural network is to extract features from the input image. Convolution preserves the spatial relationship between pixels by learning image features using small squares of input data. CNNs are regularized versions of multilayer perceptrons. Multilayer perceptrons generally means entirely linked networks, that is, each and every neuron that is present in one of the any layer is linked to all neurons in the rest of all layer. The "fully-connectedness" of these modeling networks makes all of them liable for the over-fitting cause of data. Classic ways for the regular use includes accumulation of magnitude measurement of weights by the loss function. On the other hand, CNN took an unusual move towards or step towards the regular use: they take the benefit of the current hierarchical outline in the data set and gather more and more difficult outline using smaller outlines. Thus, on comparing among the connectedness and difficulty, CNN’s are at the least limit. This type of neural network achieve good results in fields of:

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- *Identifying faces*

When the CNNs are used to identify a face (Fig. 3), firstly the detector evaluates the image at low resolution to quickly discard non-face regions and carefully analyze the hard regions at a higher resolution for accurate detection.

Fig. 3. Example of identifying faces

(A Convolutional Neural Network Cascade for Face Detection)

- *Self-driving cars*

Depth estimation is key consideration in autonomous driving as it guarantee the safety of the passengers and of the other road users. These aspects of CNN operation have been applied in projects like NVIDIA's autonomous car (Fig. 4).

The layers of the CNN make it possible for them to process inputs through multiple parameters, which makes them very flexible. Convolutional neural networks are traditionally used for image analysis and object recognition. They can detect pedestrians crossing the road in front of the car without false positives from other objects (Lin, Y., Wang, C., Chang, C. et al., 2020).

Fig. 4. Self-driving car (PBS Science Show NOVA Shines its Spotlight on Self-Driving Cars)

Another type of neural network, which finds a lot of applications is recurrent neural network (Fig. 5). Recurrent neural network (RNN) is a class of artificial neural networks where connections between nodes form a directed graph along a temporal sequence. This allows it to exhibit temporal dynamic behavior. Derived from feedforward neural networks, RNNs can use their internal state (memory) to process variable length sequences of inputs. This makes them applicable to tasks such as unsegmented, connected handwriting recognition or speech recognition. RNNs can be trained for sequence generation by processing real data sequences one step at a time and predicting what comes next.

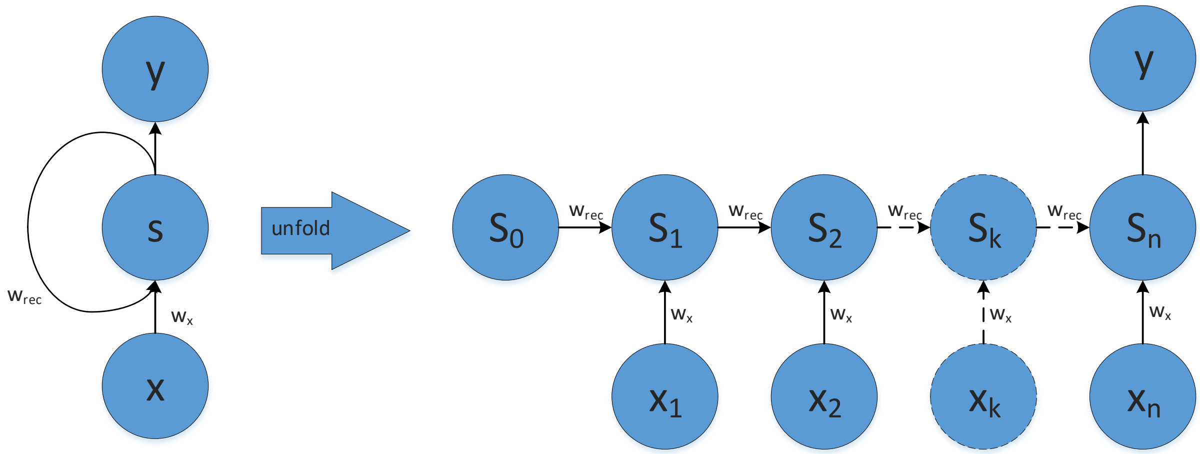

Fig. 5. Recurrent Neural Networks

Assuming the predictions are probabilistic, novel sequences can be produced from a trained network by iteratively sampling from the network's output distribution, then feeding in the sample as input at the next stage. In other words, by making the network treat its inventions as if they were actual, just like a person dreaming.

- *Language-driven image generation*

For a given text, can we learn to generate handwriting? A soft window is convoluted with the text string to fulfill this task and fed to the prediction network as an external input. At the same time as it makes the forecasts, the parameters of the window are output by the network such that an alignment between the text and the pen positions is dynamically calculated.

- *Predictions*

Given a specific input, a neural network can be trained to generate outputs that are predicted. If we have a network that fits a known sequence of values well in modeling, it can be used to predict future outcomes. The Stock Market Forecast is an obvious example.

CONCLUSION

Neural networks are broadly used for real world business problems such as sales forecasting, risk management, data validation, and client analysis. For example, neural networks are well-equipped to divide the market into distinct groups of customers based on their behavior. They can do this by segmenting clients according to basic features such as demographics, economic status, location, purchasing habits, and product attitude. The neural networks can also simultaneously consider for a product its market demand. They also can predict a customer's income, product price and etc. Neural networks have been successfully applied to issues such as pricing and hedging of derivative securities, forecasting futures prices, forecasting exchange rates, and stock performance. Traditionally, software has been guided by statistical techniques. However, these days, the underlying technologies driving decision-making are neural networks. They can help in solving ecological problems analyzing satellite images for different indicators as green areas, industrial facilities, illegal logging and so on. (Tarasov, A., Nikiforova, E., Nikiforov, M., Melnik, O., Ngongo, I. B., & Bodrov, O., 2020) They can also detect the quality condition of different transport channels like railways, highways and etc (Sadeghi, J., Askarinejad, H., 2012). Neural networks are also a trending field in medical research and it is expected that in the next few years they will be widely applied to biomedical systems.

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A Convolutional Neural Network Cascade for Face Detection

https://github.com/mks0601/A-Convolutional-Neural-Network-Cascade-for-Face-Detection

PBS Science Show NOVA Shines its Spotlight on Self-Driving Cars

https://www.roboticsbusinessreview.com/unmanned/unmanned-ground/pbs-science-show-nova-shines-its-spotlight-on-self-driving-cars/