

USING NEURAL NETWORKS MODELLING AS MOTIVATION FOR ALTERNATIVE ASSESSMENT PRACTICES IN HIGHER ENGINEERING EDUCATION

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ABSTRACT

The human brain has about 100 billion neurons. These neural networks can be simulated in the science of artificial intelligence. Thus are these mathematical models in artificial intelligence based on their biological neural network counterpart. One can use these mathematical models to model learning. Neural networks are based on collections of nodes or neurons that are connected in a tree pattern to allow communication between them. A single node is a simple processor but a multilayered network with supervised training is capable of complex tasks. Learning can be divided into surface or deep learning. Surface learning is a low energy, low cognitive approach. Deep learning are recognized by learner's accepting personal responsibility, enjoying the experience of learning and the ability to identify where to apply learning in industry or future work. It is thus beneficial if the neural networks are stimulated to a deep, constructive learning approach. Assessment can be a good method to shape learning. This article argues that by shifting to an alternative assessment approach one can shift a learner's neural networks from surface learning to deep constructive learning.

1. INTRODUCTION

It is possible to shift learner's neural networks from surface learning to deep, constructive learning with assessment. To achieve this one must not only consider and understand the psychology of the human brain but also the mathematical model of it.

2. BACKGROUND

2.1 Surface learning and deep, constructive learning

The human brain has about 100 billion neurons. Neurons are specialized to carry "messages" through an electrochemical process (Spitzer 2000: i). Neurons are interconnected along axons. The centre of a neuron receives stimuli and decides, whether or not to send a signal to neighbouring neurons (Anderson 1995: 4). These neurons are interconnected in a network. These neural networks can be simulated and are even applied in the science of artificial intelligence (Callan 2003:4).

Neural networks are based on collections of nodes or neurons that are connected in a tree pattern to allow communication between them (Callan 2003: 287). A single node is a simple processor, computing by combining the input signals with an activation rule to produce an output signal (Callan 2003: 287).

A single network node would be as follows:

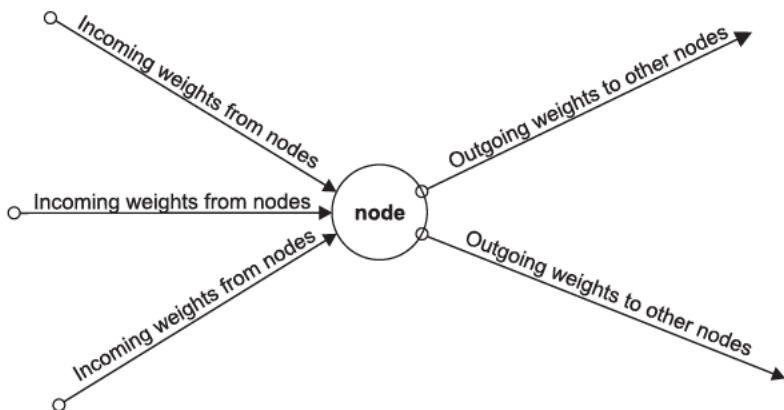


Figure 1-1: a single node

These nodes are interconnected with weighted connections. A weight is a multiplying constant for the connection's input. Singularly these nodes are limited in operation but by inter-connecting, it gives them the ability to perform complicated tasks. A multilayered network with supervised training is thus capable of learning a required function. This is accomplished by calculating the error at each net or node. The weights are slowly adjusted at every learning cycle accordingly to produce all the required outputs.

The output of a neural network is in a, prediction format. For instance, if one wants a certain answer to be *true*, depending on criteria and learning, can the network, for argument sake, be 80% convince that the required answer is indeed true. For example: a learner starts to learn to read and write for the first time. The educator might show him or her, the letter "a". If it is the first time that the learner sees this, he or she might only be 10% convince that is the letter "a" (if asked what it is). But the more the learner work with it the more he or she is convinced that this is the letter "a". This continue up until the point where the learners neural networks had enough training cycles to be a 100% sure of it.

This process can be mathematically simulated with the formula of the neuron as follows (Callan 2003: 290):

$$\text{net}_j := \sum_{i=1}^N x_{i,j} w_{i,j} \quad 2-1$$

Where:

N is the amount of inputs
 i is the node number for a specific input
 j is the number of the net
 x is the input value
 w is weights or constants

This is commonly put through a sigmoid function. The sigmoid is as follows (Callan 2003: 292).

$$f_j := \frac{1}{1 + [e^{(-\text{net}_j)}]} \quad 2-2$$

Where:

net is the output of the net
 j is the number of the net

To calculate the error it uses a generalization of the delta rule (Callan 2003: 297) (Chuavin 1995:251).

Starting at the last layer with:

$$\delta_j := (t_j - o_j) o_j (1 - o_j) \quad 2-3$$

Where:

t is the required output
 o is the net output
 j is the number of the net

The error at the hidden layers is calculated next (Callan 2003: 303):

$$\delta_j := o_j (1 - o_j) \sum_k \delta_k w_{j,k} \quad 2-4$$

Where
 o is the net output

j is the number of the net

k is the number of the net from where the error originates

δ_k is the error from the previous layer

l is the number of that specific path

The weight change for each node is then calculated with (Callan 2003: 303):

$$\Delta w_{i,j} := \eta \cdot (x_{i,j} \cdot \delta_j) \quad 2-5$$

Where:

η is the learning rate

i is the node number for a specific input

j is the number of the net

x is the input value

δ is the error from the each layer

The weights are now adjusted as follows (Callan 2003: 304):

$$W_{i,j} := w_{i,j} + \Delta w_{i,j} \quad 2-6$$

Where:

Δw is the weight change

w is the old weights

As stated can learning be divided into two approaches, namely: (Biggs 2007:19-25)(Rust 2002:148-151)(Santrock 2008: 100);

- Surface learning where learners:
 - Rely primarily on memory
 - Studying at the last minute with the minimum energy spend
 - Low cognitive levels
- Deep, constructive learning where learners:
 - Accept personal responsibility for understanding course ideas
 - A joyful experience of learning actively
 - Identify where to apply learning in industry or future work place

In surface learning is the learning rate (in equation 2- 5) moderate. The problem is that this has a low cognitive and minimum energy spend learning approach. This results in that the network only do enough learning cycles to produce the lowest expectable prediction-percentage of the correct answer. This might be as low is 51%. If this network has a single task to learn it would start adjusting the weights to give the answer and even if it is only 51 % sure of it, it would still be the correct one.

The problem is, that the weights (w) did not adjust sufficiently to produce a good prediction value for the required answer. Producing a good prediction of the answer again if a new task is learned would be problematic, especially if the new task does not build on the previous task. In deep, constructive learning, the student must be able to identify how previous knowledge can be applied to future knowledge.

It is stated that assessment can be a tool for learning (Brown 2001:6-7). By shifting to an alternative assessment approach one can shift a learner's persuasion, commitment and stimulate the neural networks, from surface learning to deep constructive learning.

2.2 Conventional vs. alternative instruments for the assessment of student learning

Conventionally were tests and examinations the only instruments, but alternative instruments of assessment are open book exams (Race, 1995 p4), reports, portfolios (SAQA 2001), presentations (Race 1995, p 10) and Vivas (Race 1995, p 11). There are a few more but are beyond the scope of this study.

2. METHODS

The following examples of alternative assessment illustrate and argue how it can stimulate deep, constructive learning.

2.1 Open book exams or a report

Consider this example question for a real world application or system:

Some aeroplanes have retractable gear that decrease drag and protect the rubber tires from the elements of high altitude flight. This landing gear is operated by electric motors or hydraulic actuators. Failures do occur. Aproximately 100 gear-up landing incidents happened annually in the United States as seen between 1998 and 2003 (http://asrs.arc.nasa.gov/callback_issues/cb_292.htm).

If a failure of these systems occurs the pilot need to be alerted to take preventive manoeuvres that might include a belly landing, landing gear can be powered from multiple sources or an emergency extension system that is a manually-operated crank or pump, or a mechanical free-fall mechanism which disengages the uplocks and allows the landing gear to fall due to gravity (http://en.wikipedia.org/wiki/Belly_landing). See Figure 3-1 of a plane taking preventive manoeuvres:



Figure 3-1: an aeroplane landing with a malfunctioning landing gear
<http://en.wikipedia.org/wiki/File:JetBlue292Landing.jpg>

Design a landing gear warning indicator system for an airplane. This landing gear indicator system should consist of:

- Indicators on an airplane blue print, for the cockpit, showing which gear is up or down
- Indicator if all the gear is up or down
- Error indicator if not all the gear is up or down

This, as an open book question would mean that the learner would have all the necessary data sheets of components to design the circuit.

The motivation how these alternative assessment methods stimulate the neural networks for deep learning are as follow:

The introduction of the danger (and the feeling of the learner that he or she might save the situation) alerts the neural networks that this is important and a good prediction percentage or low margin of error is needed. Thus the error values at equation 2-3 and 2-4 must be as small as possible. The net's weights are only adjusted at a learning rate as seen in equation 2-5 and equation 2-6 for each learning cycle. As stated would the percentage of prediction be larger and the final weights that produce the smaller error would necessitate a larger amount of training cycles.

More training cycles will result in higher cognitive levels, more energy spent and the joy and self-worth for designing a life saving system, all characteristics of deep learning.

The human brain consists of many multilayered interconnected neural networks. The images stimulate the creative neural network and improve the communication between the creative and analytical networks. The creative network run trough scenarios and by eliminating non-working ones it learn, by adjusting the weights with equation 2-3 to 2-6, when facing something similar in future. If the analytical neural network receives a scenario it calculates (with the aid of a PC, calculator or paper). The more it does these the better the weights are adapting do accomplish this. The communication networks, between the creative networks and analytical networks, weights adapt resulting in fewer non-working scenarios.

Memory networks are called on for prior learning to fuel scenarios. When these networks are revisited they would be refreshed, inserting a few training cycles improving the weights for a better prediction percentage for future reverence. If a specific scenario worked will it trigger the weights to learn with moderate training cycles so that any similar problem in future can be solved with or something similar to it (which start new possible scenarios). All these are indicators of deep learning. Thus by giving the information on how the emergency procedures work, with images, the learner would visualize where this systems are in the plane and where the wiring should go. It might even stimulate the thinking process for a possible solution with an entrepreneurial possibility for this or similar application.

These images and application are suggestive (as in hypnosis suggestion). This entails that every time the leaner see a plane, wheel, pilot, and the components of a circuit, sparks or any other stimuli that was in this example, would the neural network be refreshed and automatically get a few extra training cycles.

3.2 Presentations and Vivas

Alternative assessment methods that also stimulate the neural networks for deep learning are presentations and vivas. The learner presents the system as he or she designed it for 3.1. These include presentation on the operation and a workshop manual for software, project or system. A Viva will follow the presentation where agents can interview the learner.

If a learner is going to present in front of people (or a specialized audience), will the vulnerability factor alert the neural networks to be surer of facts, systems or content. This would initiate more training cycles. The experience of the day would stimulate the long-term memory networks that are responsible for remembering experiences. The learner also think back to the design refreshing all the networks as discussed in 3.1.

3.3 Portfolios

The portfolio is a collection of the different types of evidence for the system in 3.1. This include, photographs of the circuit built, screen shots and or video of the application, the actual application software, the power point or presentation, a report, circuit diagrams and circuit simulations. The photographs stimulate the memory neural networks, refreshing the weights and creative networks for taking the photo. Learners also take the pictures with their cell phones. This adds the cell phone as a suggestion stimulus (if the learners see there phone they would remember the task and refresh the neural networks).

The photos may also be on their phone where they might stumble on it again in future. The evidence of presentation would trigger the memories of the day and refreshing the weights. The neural networks are assured that results given at the presentation was good and extra training cycles are added. When learner present they understand, which is a higher level of learning. The report including the circuit diagrams and simulations would necessitate the recall of prior knowledge. The successful implantation of system with the prior knowledge validates it. This adds training cycles to the neural networks since it know that it works. The repetition also adds training.

4. CONCLUSION

Deep, constructive learning can be achieved by aligning assessment to stimulate neural networks to spend more learning cycles on topics. By using detailed real applications with images, different neural networks can communicate with each other. This results in learning to be creative and analytical.

Suggestion adds training cycles as stimuli that in turn refresh learning. Suggestion can be achieved by planning questioning, full of images and everyday occurrences.

For example: Give a task to plan or to do an engineering design or application for a well-known soft drink bottling plant. As prove of the power of this, you as reader would, every time you in future enjoy a soft drink think back to this. Actually if you as reader see any suggestion stimuli like an aeroplane or a learner that learn to read, a cell phone camera, presentation or portfolio etc, you would think back to this article. Suggestion thus results in prolonged learning.

Remembering refreshes the trail of thought and adding learning cycles for the neural networks. As stated one should not only consider the psychology of the human brain but also the mathematical model of it.

When keeping the mathematical model in mind with alternative assessment one can use it as a tool for shifting from surface learning to deep, constructive learning.

5. REFERENCES

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