Веселін ПЕТРОВ

КОРНІ ПРИКЛАДНОЇ ФІЛОСОФІЇ ТА ЇЇ ЗНАЧЕННЯ ДЛЯ СУСПІЛЬСТВА

Анотація. Стаття присвячена актуальним питанням походження прикладної філософії та її ролі у суспільстві. Підкреслюється важлива роль знань у сучасному суспільстві. Обговорюються поняття теоретичної і прикладної науки, а також прикладної філософії. Зауважується, що прикладне знання можна вважати філософським знанням третього порядку, яке неминуче веде до повної «істини», застосовної завжди і скрізь. Розглядається розвиток прикладної філософії та її зв'язок з прикладною етикою, адже прикладна філософія розвивалася насамперед у таких областях, як етика, оскільки концепція прикладної етики була затверджена більше п'ятдесяти років тому. Наводяться сучасні приклади розвитку прикладної філософії, зокрема: діяльність Центру прикладної філософії в Австралії, Товариства прикладної філософії у Великій Британії, видання Журналу прикладної філософії з 1984 р.

Сформульовано тезу про те, що у сучасному світі будь-яке знання є в певному сенсі прикладною філософією. Відзначається, що навіть у найабстрактнішій галузі філософії – онтології та метафізиці – став широко утверджуватися прикладний підхід, отже можна говорити про прикладну онтологію та прикладну метафізику. Хоча ідеї прикладної філософії та більш конкретно прикладної онтології та прикладної метафізики широко розвинуті лише в останні кілька десятиліть, вони мають більш глибоке і давнє коріння. Також в останні два десятиліття почала розвиватися і набувати поширення прикладна епістемологія.

Наголошується, що в сучасному суспільстві, заснованому на знаннях, настав час усвідомити не лише можливість, а й реальне функціонування філософії як прикладної філософії. Правильний підхід полягає у співпраці та взаємодії філософів з ученими, які є спеціалістами в конкретних науках, бо тільки так можна гарантувати, що філософське знання не буде неправильно витлумачено або використано, і воно знайде своє відповідне місце в сучасних дослідженнях і розробках на благо суспільства в цілому.

Ключові слова: *прикладна філософія, прикладна онтологія, прикладна метафізика.*

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NEURONS, NETWORKS AND NEXUS

Abstract. The article discusses the problems of development of artificial neural networks (ANN) in the context of the methodology of AN Whitehead. The idea that nature itself controls the learning process boils down to pantheism or atheism from a theological point of view; because outside nature no other control mechanism is involved. On the other hand, assuming the existence of an expert, there is an approach different from ANN. It makes sense to reduce the notion of the expert not only to his systematic functions, but also to include in him additional human qualities that, if desired, could bring him closer to a personal God.

The article is devoted to the consideration of software possibilities of connectionism for thinking process. The author argues that there are clear differences between the concept of Whitehead and ANN, because in the case of ANN is only about the most accurate and effective study of a goal, whatever it may be, while Whitehead deals with the aesthetic intensification of global contrasts. Gradual regulation of neuronal weights is only an expression of learning progress without any additional aspects. For Whitehead, overall weight distribution as an expression of aesthetic harmony would be crucial for the quality of communication, for example, based on the degree of entropy, but this does not play a role in the quality of ANN, measured solely by its ability to learn. In addition, self-determination or self- realization is irrelevant to neurons as opposed to real entities. But this is also a fundamental problem for Whitehead himself, as there is no meaningful application of these terms in the field of elementary processes.

It is emphasized that the main feature of Whitehead's ontology is that the world is a disjunctively diverse set that enters into a complex unity. The same applies to the flow of neuronal data: in a new neuron, data is inherited, processed and fed into subsequent neural processes, and so on. In a broader sense, creativity is inevitable in ANN processes, because if the speed of learning is too high, the convergence of the error function is no longer guaranteed; if the speed is too low, the number of required training runs can be very large. When adjusting the weights, it can happen that the optimization is stuck in the local minimum.

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Keywords: *artificial neural networks, Whitehead, connectionism*

Introduction. In the following I would like to make a suggestion and put it up for discussion on how Whitehead's *categorial scheme (cosmology)* presented in Process and Reality (PR) can be applied to current issues that come more from the exact sciences. My aim here is to connect to the current topic of so-called *connectionism*, which is excellently suited to exemplify Whitehead's *categorial scheme*, including some of its theological implications, and thus reaffirm the *adequacy* of the scheme as intended by Whitehead (For an entry into connectionism is well suited James Garson: Connectionism. In: Edward N. Zalta (ed.): Stanford Encyclopedia of Philosophy).

So far as I see there has been no Whiteheadian effort on this issue, although the programmatic proximity to the process-relational and interconnective world view is obvious. I do not think it is an exaggeration to say that connectionism is a crucial interface between Whitehead's cosmology and a mindset which largely dominates today's Artificial-Intelligence research, and thus is the focus of public interest. In particular, neural networks (machine learning, deep learning) are able to create simulations and forecasts for complex systems and interrelationships, as in weather forecasting, medical diagnostics, economic processes or image recognition. But also philosophers are interested in neural networks because they may provide a new framework for understanding the nature of the mind and its relation to the brain insofar as the brain is a neural net, formed from massively many units (neurons) and their connections.

The purpose of the article. I would like to give a brief philosophical outline of the broad topic of connectionism in order to draw attention to its programmatic potentials for process thinking. Please note if I use very simplistic examples throughout, and perhaps overly so, then only for the purpose of easy understanding.

Formulation of the main material.

1. *The functional shift.* Connectionism is an approach to modeling cognitive systems which uses so-called artificial neuronal networks and other features of machine learning. Artificial neural networks (henceforth: ANN), i.e. networks of simple *cells/units/neurons* (henceforth: neurons) are inspired by the basic structure of the natural nervous system. The basic ideas of the artificial neuron date back to the 1940^{s} and 50^{s} (McCulloch, Pitts, Rosenblatt) and were brought to maturity by the so-called back-propagation learning algorithm by Rumelhart in the 1980^{s}.

This progress inaugurated a renaissance of ANN in a variety of disciplines using computer modeling including psychology, artificial intelligence and physics (Backpropagation or also error feedback is a common procedure for the teaching of artificial neural networks, and is applied as a generalization of the Delta learning rule to multi-layer networks. For the sake of simplicity, I will continue with examples of the Delta rule for single-layer networks).

In order to understand the philosophical meaning properly, we must first recall the intellectual situation in which the connectionist model is originally located: In my perception, around the 1940th a paradigm shift took place which led from a substance thinking to a functional/dynamic thinking, which is still determining today. Examples of the *functional paradigm* are (1) ANN which can be seen as chains of functions, which in turn can represent and learn (approximately) arbitrarily complex functions and patterns, but it must also be mentioned (2) the functional algebra of mathematical Category Theory (McLane, Eilenberg), the preferred mathematical approach today, and of course (3) the Lambda Calculus (Church, Kleene), having influenced functional programming essentially – and much more, I must limit myself here. Whitehead's *process philosophy* in PR – next to Cassirer's *Substanzbegriff und Funktionsbegriff* – was the prominent *metaphysical* forerunner around the 20th, insofar as his ontology is based on *simple abstract functional input-output cells/units* (Whitehead: *actual entities/occasions*), whose connection (Whitehead: *nexus*) forms a kind of abstract neural network (chains of functions). Forward-looking views of the techniques of Category Theory or ANN, however, cannot be suspected in Whitehead; he just provided the appropriate metaphysics in his PR.

Since the matter is very complex, I will confine myself to a small example from Category Theory, just to give an impression of this paradigm shift, before I return to ANN. From the late 19th century (Cantor, Peano, Frege, Russell etc.) it was clear that all mathematics could be built on set theory using the elementary relationship $\in$, a two-digit logical relation between an individual and the set to which the individual belongs. The ontological intuition underlying the relation $\in$ is that of substance and property (intension, quality) or the corresponding set (extension. quantity), according to which the substance is that which persists in time, and the quality is that which changes in time, as was customary in tradition, cf. Kant's doctrin of schematism. The logical expression of this is the so-called predicate calculus. The proposition e.g. that this beetle is black, is usually formalised as follows: b $\in$ beetle & b $\in$ black. The functional language of Category Theory replaces the elementary relationship $\in$ by $\rightarrow$ called "arrow" or "morphism", whereby the ontological concept of substance and property is abandoned in favor of abstract objects – without explicit internal structure – between which the arrow relation exists. Since I cannot go into details here, I will only give the diagram for the above proposition:

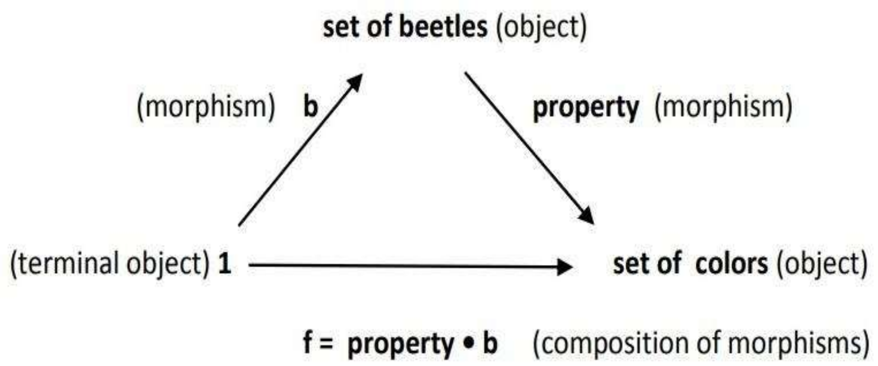


Figure 1 – Logical predicates

Note that there is no individual b, rather b is a morphism b: 1 $\rightarrow$ beetle, that means that the so-called terminal object "1" selects an instance from the object "beetle", which here is a set, and which in turn is mapped onto the set of colors. "f = quality • b" indicates that the axiomatic rule of composition of morphisms is given. So, this tiny category consists of three objects and three morphisms that meet some standard axioms of Identity, composition etc. If Whitehead calls for a new language in PR, this does not necessarily have to amount to a romanticizing metaphor; it could be that he had an arrow-theoretic dynamisation in the style of Category Theory in mind. Arrows and objects correspond to the *idea of process* rather than individuals and properties. In the case of ANN (and certainly other functional models) the bridge to Whitehead's ontology via category theory is obvious and needs no artificial reformulation as in the case of theories formulated in substance – accidence jargon. For an ANN is an object of a so-called diagram category. The objects here have the form (A -f-> B), where A is the input and B the output, f is the processor or the so-called black box. In the language of Whitehead's ontology the input corresponds to the pretensions' of an actual entity, the processor to its private process of concrescence, and the output to its objective datum. The application of Whitehead's ontology to ANN will be discussed in much greater detail below, though without making reference to Category Theory in detail; this would be an investigation in itself, which would take us too far here.

2. The natural neuron.

In the sense of an interdisciplinary approach, I would first like to recall the connection between a natural and an artificial neuron, and then subsume them under Whitehead's scheme. A natural neuron is mainly composed of three parts and an external part called synapse:

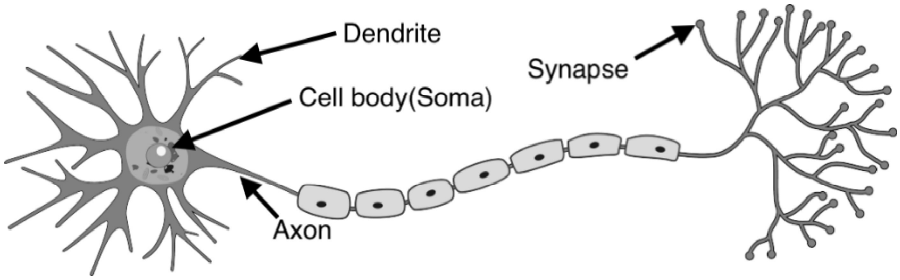


Figure 2 – Connection between a natural and an artificial neuron

1. Dendrites are responsible for getting incoming signals from outside. Soma is the cell body responsible for the processing of input signals and deciding whether a neuron should fire an output signal.

2. Axon is responsible for getting processed signals from neuron to relevant cells.

3. Synapse is the connection between an axon and other neuron dendrites. The task of receiving the incoming information is done by dendrites, and processing generally takes place in the cell body. Incoming signals can be either excitatory – which means they tend to make the neuron fire (generate an electrical impulse) – or inhibitory – which means that they tend to keep the neuron from firing. Most neurons receive many input signals throughout their dendritic ramifications. Whether or not a neuron is excited into firing an impulse depends on the sum of all of the excitatory and inhibitory signals it receives, and also on the fire threshold or bias. According to the all-or-nothing principle, the neuron discharges completely – or not at all. If the neuron does end up firing, the nerve impulse, or action potential, is conducted down the axon. Towards its end, the axon splits up into many branches and develops bulbous swellings known as axon terminals (or nerve terminals). These axon terminals make connections on target cells, such as gland cells, muscle cells or other neurons.

3. The artificial neuron.

Artificial neuron – also known as perceptron – is the *basic unit* of the artificial neural network. In simple terms, it is a mathematical function based on a model of natural neurons. An example of this is a simple logic gate/ function [henceforth: function] with binary inputs and outputs. Each artificial neuron has the following main components:

1. It takes inputs from the input layer.
2. Weighs them separately and sums them up, and
3. Pass this sum through a nonlinear function to produce output.

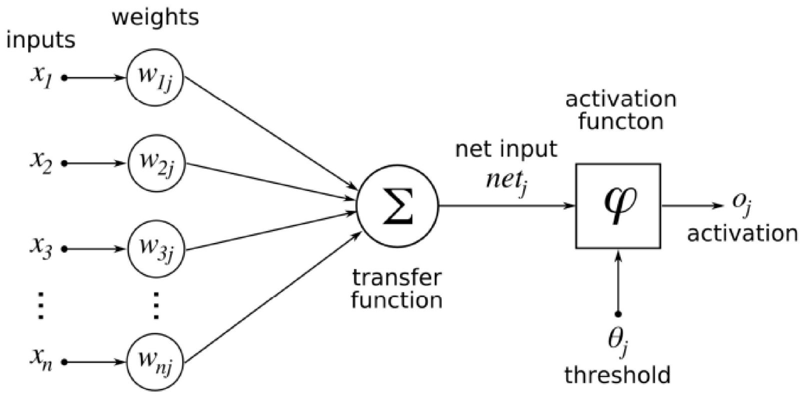


Figure 3 – Artificial neuron

The neuron/perceptron consists of four parts:

1. One input layer / Input values: input values are passed to a neuron using this layer. It might be as simple as a collection of array values. It is similar to a dendrite in natural neurons.

2. Weights and threshold:

Weights are a collection of array values which are multiplied to the respective input values. One then takes a sum of all these multiplied values which is called a weighted sum. One also speaks here of synaptic weights to draw attention to the strengthening and inhibiting effect of the synapses on the transmitted impulses. Next, one adds a threshold/bias value – representing the fire threshold of a natural neuron – to the weighted sum to get final values for prediction by the neuron.

3. Activation Function:

Activation Function decides whether or not a neuron is fired. It decides which of the output values should be generated by the neuron.

4. Output Layer:

Output layer gives the final output of a neuron which can then be passed to other neurons in the network or taken as the final output value.

Note that this simplified model does not mimic neither the creation nor the destruction of connections (dendrites or axons) between biological neurons, ignores signal timing and much more besides. However, this restricted model alone is powerful enough to work with simple classification tasks and can represent some Boolean functions like OR, AND or NAND. In order to approximate not only Boolean, but arbitrary (linear and non-linear) functions – for example by superposition of a sigmoidal function (see below) in Fourier analysis style (Cybenko, 1989) – several neurons must be interconnected to networks with at least one intermediate/hidden layer of neurons, called multilayer neurons. So, multilayer neurons contrary to single layer neurons have a kind of far-reaching *universality*. In case of a multilayer neuron, the formulas below, which refer to a single layer neuron, have to be modified a bit, which I will refrain from here for the sake of simplicity.

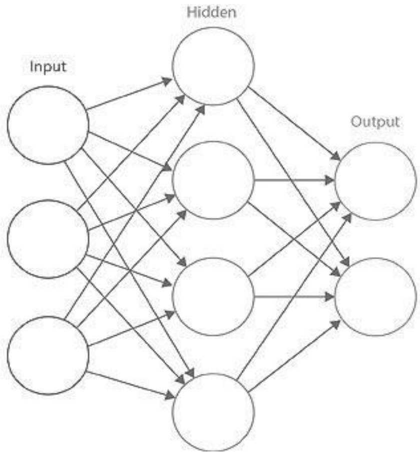


Figure 4 – Parts of the neuron

Let us now take a closer look at how neurons work. The neuron is introduced in the following way: First, the activation *v* (referred to as "net input" or "net" in the figure above) of the artificial neuron is defined by:

$$v = \sum_{i=1}^{n} \mathrm{x_i} \cdot \mathrm{w_i} - \theta \tag{1}$$

Additional input $x_0 = 1$ – weighted by w_0 – is usually introduced as a mathematical simplification for the threshold/bias θ, so:

$$v = \sum_{i=0}^{n} \mathrm{x_i} \cdot \mathrm{w_i}$$
$$o = \varphi(v) \tag{2}$$

Where:
n: the number of inputs
x_i: the input with index i, which can be both discrete and continuous
w_i: the weighting of the input with the index i
φ: the activation function and
o: the output.

As activation function φ different function types can be used, depending on the network topology. Such a function can be non-linear, for example sigmoid, piecewise linear or a hard limit function. For the sake of simplicity we only consider the hard limit function and the sigmoid function from the set of possible functions.

$$\varphi^{\text{hlim}}(v) = \begin{pmatrix} 1 & \text{if } v \geq 0 \\ 0 & \text{if } v < 0 \end{pmatrix} \qquad (3)$$

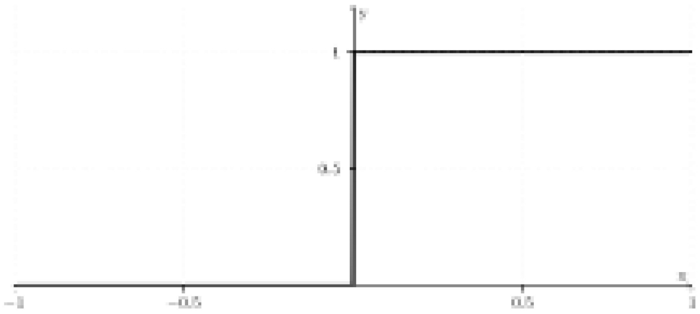


Figure 5 – Limit function

The hard limit function, as defined below, takes only the values 0 or 1. The value 1 for the input v ≥ 0, otherwise 0. With subtractive use of a threshold value θ, the function is only activated if the additional input exceeds the threshold value. A neuron with such a function reflects the *all-or-nothing property* of the biological neuron. Sigmoid functions as activation function are very often used. As defined here, they have a variable slope *a* which influences the curvature of the function graph. A special property is their differentiability, which is required for some procedures such as the back-propagation algorithm.

$$\varphi_{a}^{sig}(v) = \frac{1}{1+\exp(-av)} \qquad (4)$$

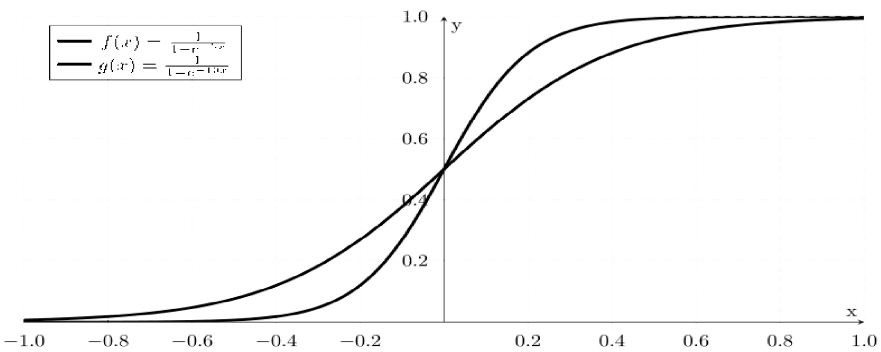


Figure 6 – Sigmoid function

The values of the above functions are in the interval [0, 1]. For the interval [- 1, + 1] these functions can be defined accordingly.
Single artificial neurons can be used to represent some Boolean functions – here, the three functions conjunction (AND), disjunction (OR) and negation (NOT) can be represented using a threshold and φ^{hlim} as follows:

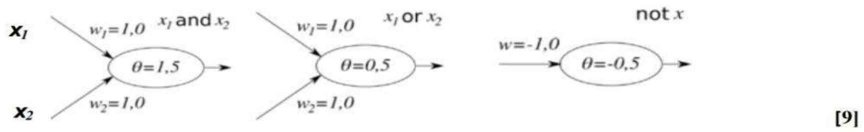


Figure 7 – Boolean functions

For the AND function, for example, it can easily be seen that only for the Boolean inputs $x_1 = 1$ and $x_2 = 1$ activation is 1, otherwise 0.

$$o = \varphi^{\text{hlim}}\left((w_1 \cdot x_1 + w_2 \cdot x_2) - \theta\right) = \varphi^{\text{hlim}}\left((1.0 \cdot 1 + 1.0 \cdot 1) - 1.5\right) = \varphi^{\text{hlim}}(0.5) = 1 \quad (5)$$

In contrast to the previous example, in which the appropriate weights were given externally, neurons have the fascinating property of learning the function to be represented. The weights and the threshold are initially assigned random values and then adjusted using a learning algorithm. To learn the AND function above, the so-called Delta learning rule can be applied. This learning rule finds its psychological counterpart in the learning rule according to Hebb. It adds the values of incorrectly recognized inputs to the weights to improve recognition until all inputs are correctly classified. The activation function here is the function φ^{hlim} analogous to the previous example – under certain conditions one could choose φ_{α}^{sig} as well. For the learning procedure, the learning rate, which determines the speed of the learning process, is defined here with $\alpha = 1$. Thus, there is no explicit mention of it. Instead of specifying the threshold value as such, an additional neuron (bias), i.e. a constant input $x_0 = 1$ is added specified by the weight $w_0 = - \theta$.

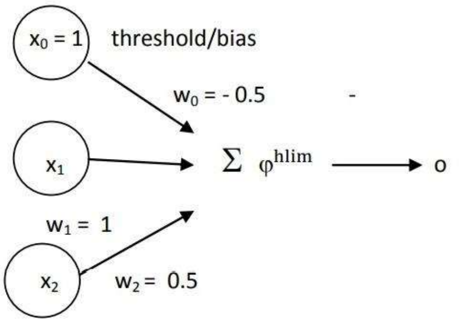
The delta learning rule can be expressed briefly as follows

$$W^{new} = W^{old} + \Delta W \quad (6)$$

By adding the incorrectly recognized inputs, the corresponding weights are corrected by

$$w_i^{new} = w_i^{old} + \sum_j \alpha \cdot (t_j - o_j) \cdot x_i \quad (7)$$

where:
j: the number of the input,
t_j: the desired output (target),
o_j: the actual output
x_i: the input and



[12]

$\alpha < 0$: the learning rate coefficient

For the AND function with the corresponding initial random weights the teach-in table then looks like this how to calculate easily:

Table 1

epoch	X_0	X_1	X_2	W_0	W_1	W_2	*sum*	*Actual o*	*Target o*
1	1	**0**	**0**	- 0.5	1	0.5	-0.5	0	**0**
	1	**1**	**0**	+1	1	0.5	2	1	**0 error**
	1	**0**	**1**	0	0	0.5	0.5	1	**0 error**
	1	**1**	**1**	-1	0	-0.5	-1.5	0	**1 error**
epoch	X_0	X_1	X_2	W_0	W_1	W_2	*sum*	*Actual o*	*Target o*
2	1	**0**	**0**	- 0.5	1	0.5	-0.5	0	**0**
	1	**1**	**0**	- 0.5	1	0.5	0.5	1	**0 error**
	1	**0**	**1**	-1.5	1	0.5	-2	0	**0**
	1	**1**	**1**	-1.5	1	-0.5	0	0	**1 error**
epoch	X_0	X_1	X_2	W_0	W_1	W_2	*sum*	*Actual o*	*Target o*
3	1	**0**	**0**	-1.5	1	0.5	-1.5	0	**0**
	1	**1**	**0**	-1.5	1	0.5	-0.5	0	**0**
	1	**0**	**1**	-1.5	1	0.5	-1	0	**0**
	1	**1**	**1**	-1.5	1	0.5	0	1	**1**

The neuron has learned to represent the AND function as in the first example, but without specifying certain weights in advance. It iterates the adjustment of the weights according to the learning rule until the actual values match the target values. The term "epoch" refers to one cycle through the full training dataset, here the four truth value distributions of the AND function. Usually, training a neural network takes more than a few epochs as in this little example. Further, one should feed the training data in different patterns for a better generalization when given a new "unseen" input (test data); for reasons of simplicity this variation of test data is left out here; they always have the same order. When the learning goal is reached, the training phase is over. That this – in principle – always succeeds is shown by the proof of the important *convergence theorem* for the learning of the neuron: every function that can be represented, can be learned! (Rosenblatt, 1958) An artificial neuron is able to learn some functions by machine even without an entire network. However, a *single* neuron is not able to learn *every* function so that multilayer neurons are inevitable; we will illustrate this with the example of the AND and XOR (exclusive OR: either/or) function.

Let us compare the AND function with the XOR function using the corresponding truth tables:

AND	x_1	x_2	XOR	x_1	x_2
0	0	0	0	0	0
0	1	0	1	1	0
0	0	1	1	0	1
1	1	1	0	1	1

(14)

For these truth tables to be fulfilled, the corresponding weights and thresholds must be chosen so that each row of the tables is fulfilled by it. In the case of the AND function this means:

$0 \cdot w1 + 0 \cdot w2 < \theta$

$0 \cdot w1 + 1 \cdot w2 < \theta$

$1 \cdot w1 + 0 \cdot w2 < \theta$

$1 \cdot w1 + 1 \cdot w2 \geq \theta$

This holds obviously always if w_1, w_2 and θ are chosen so that $w_1 < \theta$, $w_2 < \theta$ and $w_1 + w_2 \geq \theta$ applies. Every choice of weights that fulfills this condition realizes the logical AND function. Here it becomes clear that there is more than one solution to realization of the AND function.

The XOR function meets the conditions:

$0 \cdot w_1 + 0 \cdot w_2 < \theta$

$0 \cdot w_1 + 1 \cdot w_2 \geq \theta$

$1 \cdot w_1 + 0 \cdot w_2 \geq \theta$

$1 \cdot w_1 + 1 \cdot w_2 < \theta$

This can only be achieved if $w_1 \geq \theta$, $w_2 \geq \theta$ and $w_1 + w_2 < \theta$. But, these conditions do not apply to any possible choice of w_1, w_2 and θ. The solution space is empty: A network consisting of a single neuron representing the XOR function does not exist in principle. For a multilayer neuron this problem does not exist. So we go to the multilayer neuron.

The Boolean formula of a XOR function is:

(x_1 and (not x_2)) or ((not x_1) and x_2) – what does say: either x_1 or x_2

We simplify this expression to:

(x_1 or x_2) and (not (x_1 and x_2)).

From this simplified expression, we can see that the XOR function consists of an OR function, a NAND (= NOT(AND)) function and an AND function. (But also a combination of AND, OR and NOT works here. There are various ways and values to achieve Boolean functions). This means we will have to combine two neurons:

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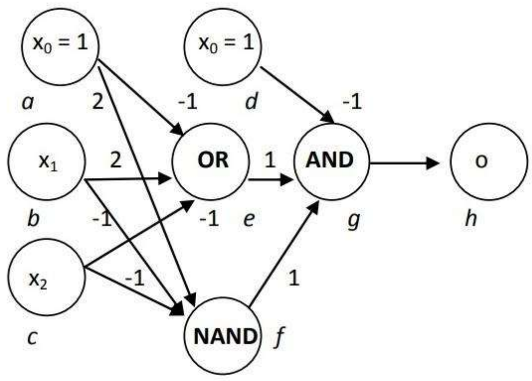

Figure 9 – Combination of AND, OR and NOT

As it is important for further considerations, let us keep in mind that NAND and NOR functions are *universal* for computation insofar as any Boolean function, however complex, can be composed of NAND and NOR functions. The proof is easy to provide via appropriate truth tables. It follows that neural networks are *universal* for Boolean computation.

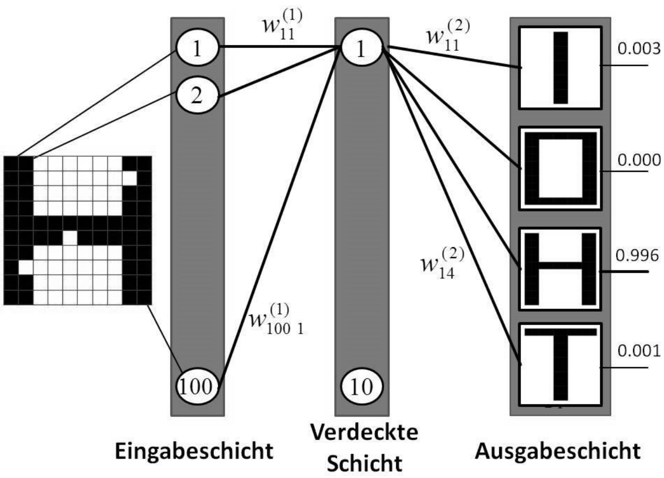

Figure 10 – Boolean computation

Based on the last network, you now have at least an impression of how pattern recognition basically works. This net here has as input not two but 100 pixels (10×10) with two states (1,0 = white, black) and as output not two (1,0) but 4 identifiers (I,O, H, T), which can be approximated by the net. No matter into which dimensions one enters, the idea of the ANN always remains the same; more cannot be shown here.

Finally, it should be mentioned that the learning process, as far as it has been discussed here, corresponds to so-called *supervised machine learning* – it describes the recognition of correlations in data sets. In contrast to unsupervised machine learning, both the input and the output are already present in the form of a data set. The algorithms learn (train) the relationship between input (features) and output (label) in these data. After the teach-in phase, the trained algorithm can be applied to new input data to predict a result based on the learned relationships. Supervised learning means that the network is trained under the guidance of a *supervisor*, who can be an *expert* but also *selective environmental conditions*, leading the inputs deliver to the desired outputs. The training process can be visualized clearly using the flowchart for ANN learning through back-propagation resp. Delta-rule.

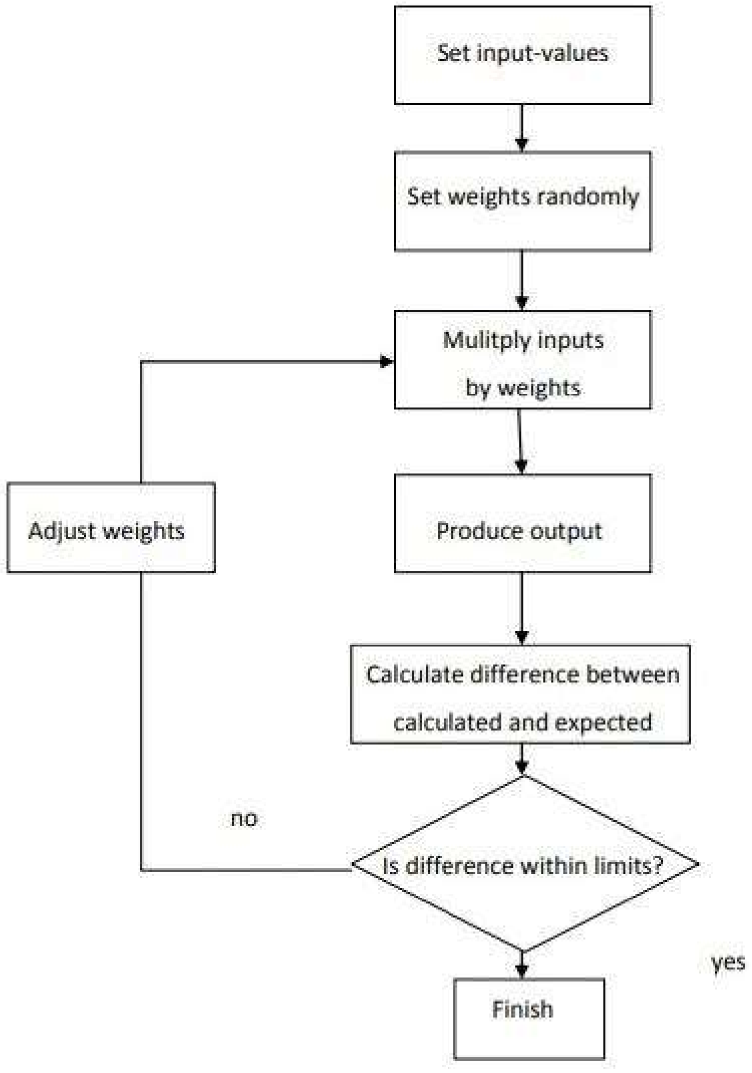

Figure 11 – Supervised machine learning

4. Whitehead's Ontology and ANN

Recent developments in the sciences, e.g. quantum physics or ANN, offer many opportunities for metaphysical interpretations beyond mere materialism – and since there are no standard limits to interpretation; there is a danger that scientific models will be overly charged with metaphor and intimated into ideological constructs of meaning and wishful thinking. This brings to mind the skepticism of many scientists towards metaphysics in

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general. In my understanding, there are at least two rational variants of metaphysics, though: 1. the transcendental approach (Kant), which analyses the conditions of the possibility of scientific knowledge, and 2. The inductive approach, which seeks analogous extensions of the relevant models – also into other disciplines – under guidance of a flexible ontological scheme (Whitehead).

In the sense of the latter, I would now like to extend the analogy between natural and artificial networks into the ontological realm, pointing to their common analogy to Whitehead's actual entities and nexus as superordinate categories. Since I have to be brief, I can bring no more than a superficial sketch of Whitehead's ontology tailored to the intended points of comparison regarding ANN. Certainly, there is much more to be said and discussed here, but this will have to be postponed until later.

a. Actual Entities and Neurons

Already the structural sketch of an actual entity reveals a similarity to the above sketches of a natural and biological neuron.

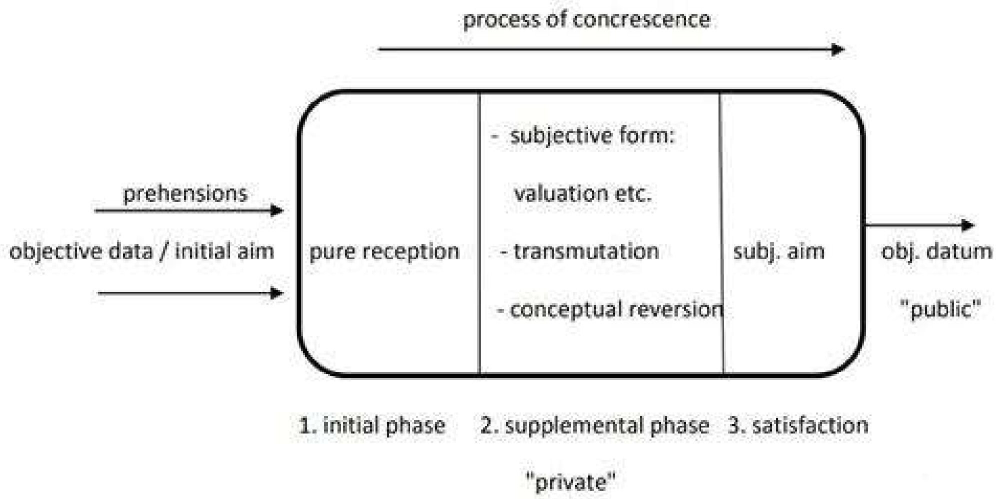

Figure 12 – Structural sketch

Let us be a bit more precise: According to Whitehead, the so-called actual entities are atomic processes, which are isomorphic to each other, on which the whole reality is based. They should not be hypostasized in any case, but rather they are to be understood as regulative ideas or guidelines, under which real existing processes, as they occur e.g. in elementary particle physics, are to be considered. But one can also find examples of actual entities in *model worlds*, such as the Cellular Automata or as here in the world of ANN – nevertheless, one must be aware that Whitehead's primary intention was physical applications (For a modeling of Whitehead's ontology using cellular automata see: Michael Rahnfeld: Cellular Automata, in: Science and Mind in Contemporary Process Thought, ed. by Jakub Dziadkowiec and Lukasz Lamz, 2019).

An actual entity is a process of concrescence (growing together), in which initial data are causally absorbed and finally processed towards a subjective aim. (1) In the first phase of this process, the output data of other actual entities, which are objectively available (public), are prehended or felt (positively or negatively by exclusion), purely receptively. They are simply re-enacted (reactivated) without further modifications. Among the initial data is also the prehension of the divine actual entity (God), who is the carrier of all eternal objects (i. e. conceptual forms in the broadest sense) and provides the initial aim in question. The initial aim is a set of eternal objects, which guide the individual concrescence. This set of eternal objects is derived from a somehow ordered class of *all* eternal objects, where the selection criterion depends on the relevance of the eternal objects to be selected for achieving the individual concrescence goal. This means that with this selection the *ideal of development*, called subjective aim, is given.

(2) In the supplemental phase (private), the data are processed according to the subjective form of the actual entity, i.e.

(a) the relevant properties respective eternal objects of the distinct prehended data are abstracted from the data and transmuted or combined into a unit (nexus).

(b) Furthermore, the properties are valuated with respect to the achievement of the subjective aim.

(c) It may be the case that the valuations of the data, as they were made by previous actual entities, are revised and that the same properties of the data are valuated differently in respect to their processing function (conceptual reversion).

(3) In the completion phase (satisfaction) the subjective aim is achieved at best, i.e. that the processing of the data according to the subjective form is completed and the ideal of concrescence has been realized. Logically, the potential form of the actual entity in question has become a fully determined proposition the result of which ("superject") in turn serves as an objective datum for further actual entities, i.e. it can then be objectified as one of their data.

Regarding the temporal aspect (and similarly the spatial aspect) of actual entities the following can be stated: Time is commonly measured in periods of a process, where for the sake of accuracy processes with smallest possible periods are chosen, whose durations are set to 1 by convention, i.e. the duration itself is not an object of time measurement. In this sense, the actual entities as atomic processes do not have any time phases themselves, but they may have systematic phases like the stages of the concrescence, which can be distinguished at the actual entities (see above). Whitehead calls these phases" *epochs*. The time flow is defined by the sequence of the epochs of actual entities which stand in *internal relation* to each other, as far as the one "grows out" of the other as shown above. Since time is thus discrete, paradoxes such as that of Achill and the turtle become obsolete.

If you look back to Figure 3, you can see that neurons can more or less be subsumed under the scheme of an actual entity. Neurons are therefore also suitable from a didactic point of view to exemplify and illustrate Whitehead's terminology. First of all it must be stressed, that the neuron here may *not* be interpreted as material switching element, although in other contexts such interpretation has priority; here the neuron has to be understood as a *temporal process of a flow of data*, which starts with an "publicly given" input that is processed "privately" and ends with a "public" output in the sense of Whitehead's *epoch* of an actual entity. Please note, that the Whiteheadian term "epoch" has a slightly different meaning here than in Table 1 where the technical term "epoch" refers not to one single neuron but to one cycle through the full training dataset.

− A bit more precise: (1) in the first phase, the neuron receives a data input, which in turn comes from other neurons, except for the first (and last) layer, which is an interface to the supervisor (e.g. expert). Furthermore, in this phase the neuron receives also its program from a supervisor or a programmer – esp. its special threshold and its special type of activation function (out of a systematic ordering of such functions), determining the data flow with regard to a goal to be achieved: the analogy to Whitehead's initial aim is obvious. Systematically speaking, the supervisor takes the position of Whitehead's God here, insofar as he designs the programs of individual neurons and their interaction according to his ideas of an ideal to be achieved. (2) In the second phase the relevant properties of the data, which in the case of ANN are all numbers, are individually weighted, also by numbers. The weightings do not happen randomly, but are to be interpreted in a final sense as the result of a directed learning process (Table 1) in which the respective neuron participates. Then, the numerical values of the weighted data are summed up to a single value corresponding to Whitehead's transmutation. At this place an interpretation of the notion "negative prehension" is possible, that is such a prehension, whose datum gets the weight 0 and thus is not included in further processing, thus has no influence to the output. You can also see that the activation function and the threshold/bias have a lot to do with what Whitehead calls a *decision*: they decide when the neuron fires, i.e. which of the output values should be generated by the neuron. In special cases it is conceivable that the activation function and the threshold/bias, which have been brought into play for the general case, may have to be replaced by others, i.e. that the previous program is revised, which is close to the *conceptual reversion* of Whitehead. (3) In the last phase the output data can be passed to other neurons as input data, or in the case of the final output to the supervisor that compares them with the ideal he has set.

− From a logical perspective in the sense of Whitehead, it is advisable to look at the formulas 2 and 6. Formula 2 is the most general expression for the uninterpreted proposition of a neuron; it quasi mirrors the complex eternal object, which defines the process, and in terms of its interpretations it can be understood as a general "lure for feeling" – as Whitehead puts it – towards its self-realization. Formula 6 shows this process of self-realization for the concrete case of an AND-neuron: the target/output (o=1) is realized by the neuron's feelings or prehensions of the respective input data (x_1=1, x_2=1), as well as the conceptual prehensions, i.e. the activation function φ^{hlim}, the threshold = 1.5 and the weights w_1 = 1.0, w_2 = 1.0. Just as in the case of an actual entity the potential form of the neuron in question has become a fully determined proposition by this interpretation, result of which may serves as an input for further neurons or as final output.

b. Nexus and Networks

− A nexus is composed of actual entities that are connected (directly or indirectly) by internal relations, i.e. prehensions. For example, all actual entities, which lie in the "prehension-cone" of the past of a certain actual entity, form a nexus. However, those actual entities, which are simultaneous with this particular actual entity, do not form a nexus by direct prehensions, but possibly via indirect prehensions mediated by past or future actual entities. Formally, a nexus can be understood as a directed graph, with the actual entities as nodes and the prehensions as edges. One could even tighten it to a weighted graph by assigning numerical values to the edges, which correspond to the valuations of prehensions by the actual entities. Graph theory is closely related to topology. In graph theory, a graph is a set of points (nodes), which may be connected by lines (edges). The shape of the points and lines is not important in graph theory. Topological structures are, so to speak, consciously charged with very specific contents and relations and are exactly defined by their logical connections. A topological structure offers the advantage to manipulate spatial objects in their mutual relations without knowledge of their coordinates. Topology, in turn, is closely related to the geometry and set theory from whose concepts it emerged. These few clues may be enough to show the path Whitehead took from prehensions through nexus and topological structures to geometry in PR (Michael Rahnfeld: From Nexus to Points, 11th International Whitehead Conference, Azores, 2017).

This can be transferred to ANN: the network in Figure 9 is an example of a nexus in Whitehead's sense; thus also an example for a directed graph. We find four layers of neurons (*a, b, c* ...). The neurons within the layers are not connected directly to each other, so the processes taking place in them are simultaneous, and therefore cannot influence each other – so, they do not form sub-graphs. However, there are a lot of sub-graphs: for example, $N_1 = [a, b, c, e]$ and $N_2 = [a, b, c, f]$, where their union $N_3 = N_1 \cup N_2$ is also a directed graph, but not $N_3 = N_1 \cap N_2$ etc. One can already guess from this simple example that nexus of actual entities and graphs in ANN define both spatio-temporal *extensions* (Whitehead: *regions*) whose set-theoretic relations like union, section, complement etc. can used for the construction of a topology and perhaps higher types of geometry.

One way leads Whitehead from the nexus to geometry, another to so-called *societies*. Just a few words: the simplest form of a society consists of a nexus of single actual entities in succession, which all represents the same properties (eternal objects, propositions) during a certain period of time. Whitehead calls such a society an *enduring object* or *a personally ordered society.* The nexus is distinguished by the fact that it always has the same character, and in this respect it corresponds to what is meant in Latin persona.

Our naive intuition of constant substances is due to the grouping of such enduring objects into a unit. In ANN a simple example of an enduring object is the iterative application (chain) of the NOT-function in Figure 7: 1 → NOT → 0 → NOT → 1... Concerning the "public" (Whitehead: objective) output data this enduring object consists of the sequence of 1 and 0 (Whitehead: defining characteristic), concerning its "private" (Whitehead: formal) functions of a sequence of NOT-propositions.

A special kind of society is the *corpuscular society*, which consists of a multiplicity of enduring objects of the same type, such as in the view of substances a diamond consists of carbon atoms. In my opinion, this is adequately reflected in the application to ANN by the fact that in the range of Boolean functions, the NAND or NOR functions each form a base, i.e. any Boolean function can be expressed by NAND or NOR functions alone. In a figurative sense one can say that they are the neuronal "atoms" for "corpuscular" Boolean networks (societies). The ANN, which represents the function of a so-called half adder, is an example of a corpuscular society in Whitehead's sense, which consists solely of (chains of) NAND neurons, as shown in the sketch below. Here, all weights are set to -2 and the threshold/bias to 3.

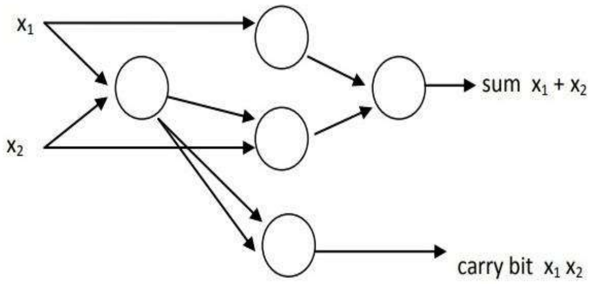

Figure 13 – Corpuscular society in the sketch

Another important type of society is the *structured society*. I am not sure whether this term, as Whitehead meant it, can be fully exemplified by ANN; nevertheless, at least partial aspects can be covered. Recall that Whitehead's original focus was on the structure of the physical world: An electron on or proton is a society of electronic or protonic occasions (actual entities). More specialized forms of social order incorporate electrons and protons into atoms, atoms into molecules, molecules into cells, and cells into bodies. In this way, a chain of complex societies results, and this means hierarchies of societies within societies. Whitehead calls such complex societies structured societies. In the world of ANN such hierarchies can partly be found, e.g. when in the image recognition of faces one layer is responsible for the recognition of the mouth, another for the recognition of the eyes etc. In order to convey this, a somewhat deeper introduction to ANN would be necessary, which I cannot provide here. However, in our tiny Boolean model world the following correspondence can be constructed: it shows a hierarchy of three neurons (NAND, OR, NAND), which together form the network for the XOR function. Metaphorically speaking, the XOR-function is an organism consisting of the organism of an AND-function, into which in turn, as organisms, the NAND and OR-functions enter. The hierarchical dependency of the parts on each other becomes clear if you write the Boolean expression for XOR as a tree, here with truth values x_1=1 and x_2 =0.

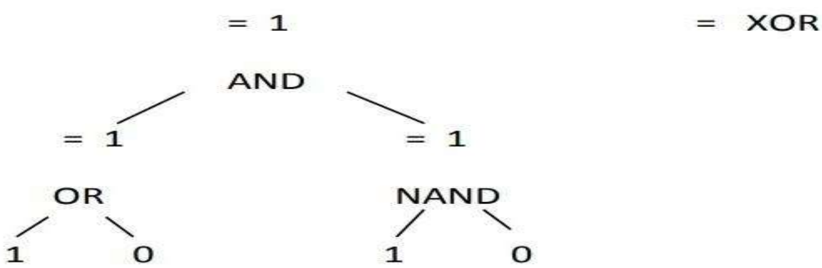

Figure 14 – Forms of society

In a similar way higher forms of society can be defined. The tendency is that modeling higher societies using simple means such as ANN becomes more difficult and less convincing the higher you go. Nevertheless, ANN appears to me in the discussion of nexus and its variants a valuable didactic tool to introduce Whitehead's ontology in precise and yet vivid terms.

c. God and the World

To make it clear from the beginning: The remarkable difference between Whitehead's physical nexus and the artificial and natural networks is that all nexus form a single overall nexus called the world or universe, whereas networks do not form a complete network, just as all brains do not form a single brain. Accordingly, for Whitehead there is a single world and thus a single god, but on the other side there are many networks and their supervisors. The following reflections on "God and the World" are therefore only of *local* significance in the case of ANN, whereas Whitehead's claim is *global*, which is more compatible with traditional concepts of God and therefore allows for a better theological bridge-building than ANN. Nevertheless, as we will see, the reflection on ANN does give rise to theological association.

First to Whitehead: Whitehead's "ontological principle" postulating that all features in the universe derive from actual entities, presupposes the existence of a *unique* actual entity as primordial source and carrier of the conceptual framework conditions of the universe. Whitehead terms this entity "the primordial nature of God". God does not act as the creator and executor of the universe, but assumes the metaphysical task of substantiating abstract conceptual forms and their potential orders. In regard to Whitehead, the abstract objects comprise essentially: (1) the "eternal objects" and their compositions entering into (2) the initial/subjective aims of actual entities as conceptual and propositional prehensions, and (3) the subjective forms of prehension.

God is not only a static metaphysical framework, but even more an active principle: to hold – with Whitehead – that God valuates all eternal objects "in their relevance for particular actualization" implies in God an activity of selection, and also an "urge towards realization of the datum conceptually prehended" and "maximum realization of value", to be understood primarily as esthetic "intensity" in terms of "balanced complexity" or "harmonic contrasts". Also, there is free space for "causa sui" – that means that God has not the capacity to impose his selection upon the actual entities forcibly, but by "lure" or "persuasion" which an actual entity may follow or not, depending on the self-determined aim of its "concrescence. In this context, the problem of the activity of God being able to perform miracles in spite of his own omniscience is discussed (Halapsis).

Besides his primordial nature, God has a "subsequent nature", prehending and valuating the actual state of the entire universe and hence of each actual entity at a time in the light of his primordial nature. According to his global subjective aim, he is updating the initial aims for all actual entities and he does so permanently, because it is up to the "creativity" of each actual entity to accept His decisions or not so that the future evolution is determined only with some probability and demands subsequent improvements by God. In this sense it is questionable whether God as an actual entity ever enters the last phase of satisfaction; for, if he entered into it, he would then have finally achieved his "subjective aim": the world would then be in a stable state of divine order which probably contradicts the individual degrees of freedom of the actual entities.

One might demand at this point the function of God to be replaced by a scientifically sound evolutionary mechanism to avoid unnecessary mystifications. However, Whitehead emphasizes expressly in *Function of Reason* that in his view the evident upward tendency via "intensity" in nature can only be explained by existence of an element of finality, a "reason" or "counter-agency" against decay beyond physical and chemical mechanisms, whatever one may choose to call it.

Now let's make the comparison to the ANN: In analogy to Whitehead's ontological principle, the neurons as well as the actual entities form the substance or the basic building blocks (atoms) for the world of an ANN, so that all further principles etc. are based on them. In analogy to Whitehead's ontological principle, the neurons form the substance or the basic building blocks for the world of an ANN, so that all further principles or considerations etc. are based on them. This substance does not owe its existence to the supervisor, who controls the learning process, but is given to him. Like Whitehead's God, he is not the creator, but the controller and coordinator of the world, who sets an ideal to be learned for certain input value, selected by him. In the sense of God's "primordial nature", the supervisor has access to a setup of a priori given concepts, such as a set of activation functions or special parameters for the learning rules etc. and in full accordance with God's "subsequent nature" he compares (via the applied learning rule) the actual outputs with the ideal in order to re-adjust the individual weights and maybe also other parameters. Both Whitehead's world and ANN move in a kind of loop (Figure 11) that leads from a constant comparison of reality and ideality to a gradual improvement of the world.

Conclusions. With regard to the set ideal, there are clear differences between Whitehead and ANN, inasmuch as in the case of the ANN it is exclusively a matter of learning as precisely and efficiently as possible about a given goal, whatever it may be, whereas Whitehead is concerned with an aesthetic intensification of the contrasts of the global nexus. The stepwise adjustment of the neuron weights is only an expression of the learning progress without any further aspects. Let us take Figure 9 as an example: for Whitehead, the overall distribution of weights as an expression of aesthetic harmony would be decisive for the quality of the nexus, e.g. on the basis of an entropy measure, but this does not play any role at all for the quality of the ANN, which is measured solely by its ability to learn. Furthermore, terms like self-determination or self-realization do not matter for neurons in contrast to actual entities. But this is also a fundamental problem for Whitehead himself, since there is no meaningful application of these terms in the field of elementary processes; rather, they seem to be reserved for higher entities.

As already mentioned, the supervisor can be a so-called *expert* or *nature* can select the actual outputs with regard to the optimal target output. The idea that nature itself controls the learning process boils down to *pantheism* or atheism from a theological point of view; for beyond nature no other control mechanism is brought into play. Thus there is no personal or personified God here. If, on the other hand, one assumes some kind of expert, which obviously corresponds to Whitehead's view, there is an entity different from the ANN, which the ANN intentionally uses for its purposes. This view leads to *pantheism*, insofar as ANN is part of the world of the expert, but is different from him and is not arbitrarily manipulated by him in terms of its existence and functioning. It makes sense to reduce the concept of the expert not only to its systematic functions, but to include in it further human qualities, which could bring him close to a personal God, if so desired. In my opinion, which of the alternatives is to be preferred cannot be decided a priori, but emerges from the overall context in which we stand and argue. It is difficult to make last words here.

Finally, a word about Whitehead's basic "Category of the Ultimate". This term comprises three components: *creativity*, *many* and *one*. This is to express the basic feature of Whitehead's ontology, according to which the world constitutes a disjunctively diverse *many* which enter into a complex unity. The novel *one* is the *creation* emerging from this concrescence, and is disjunctively diverse from the units it has unified. Mutatis mutandis the same applies to the data flow of neurons, as already shown: In a new neuron data is inherited, redesigned and supplied to subsequent neuronal processes etc. In a broader sense, creativity is inevitable in the processes of ANN as the following consideration shows: If the steps of the learning rates (Formula 7) are too large, the convergence of the error function is no longer guaranteed; if the steps are too small, the number of necessary training runs can become very large. When adjusting the weights, it can unfortunately happen that the optimization gets stuck in a so-called local minimum. Also the repetition of the method with changing, randomly distributed initial values of the weights does not always leads to a solution, since often an astronomically high number of local minima exists. In other words, the loop in Figure 11 never ends positively and therefore the initial parameters (weights, thresholds, activation functions) must be selected again. The need to overcome these and other difficulties has led to a large number of different and very specific solutions. But there is no satisfying solution on all sides. It is therefore possible that the ideal aimed for by the expert cannot be achieved due to unfavorable circumstances, although it would be possible in principle. If the ANN is put into analogy with the world and the expert with God, this means that neither the expert nor God is omnipotent and omniscient within the limits of what is actually possible; they cannot, so to speak, *force the ideal*. At best, they can do it by tentative experimentation, whereby a final solution cannot be expected for all cases. If one follows what is generally accepted as the definition of creativity, according to which creativity is the ability to create something that is new or original and at the same time useful or usable, then one can say that Whitehead's God as well as the expert in the creation of ever new nexus or networks to achieve the set ideals are in a constant creative process. Very metaphorically speaking, they are artists and not dictators.

Conflict of Interest and other Ethics Statements

The author declare no conflict of interest.

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Майкл Ранфельд

НЕЙРОНИ, МЕРЕЖИ ТА НЕКСУСИ

Анотація. В статті обговорюються проблеми розвитку штучних нейронних мереж (ІШНМ) в контексті методології А.Н. Вайтгеда. Ідея про те, що сама природа контролює процес навчання, зводиться до пантеїзму чи атеїзму з теологічної точки зору; бо поза природою жоден інший механізм контролю не задіяний. З іншого боку, якщо припустити існування якогось експерта, є сутність, відмінна від ШНМ. Має сенс звести поняття експерта не лише до його систематичних функцій, а й включити в нього додаткові людські якості, які при бажанні могли б наблизити його до особистого Бога.

Стаття присвячена розгляду програмних можливостей коннекціонізму для процесного мислення. Автор доводить, що між концепцією Вайтгеда і ШНМ є чіткі відмінності, оскільки у випадку ШНМ йдеться виключно про якомога точніше й ефективніше вивчення певної мети, якою б вона не була, тоді як Вайтгед займається естетичною інтенсифікацією контрастів глобального зв'язку. Поетапне регулювання ваг нейронів є лише виразом прогресу навчання без будь-яких додаткових аспектів. Для Вайтгеда загальний розподіл ваги як вираз естетичної гармонії мав би вирішальне значення для якості зв'язку, наприклад, на основі міри ентропії, але це не відіграє жодної ролі для якості ШНМ, яка вимірюється виключно її здатністю до навчання. Крім того, самовизначення або самореалізація не мають значення для нейронів на відміну від реальних сутностей. Але це також є фундаментальною проблемою для самого Вайтгеда, оскільки немає змістовного застосування цих термінів у сфері елементарних процесів.

Наголошено, що основною рисою онтології Вайтгеда є те, що світ являє собою диз'юнктивно різноманітну безліч, яка вступає у складну єдність. Те саме стосується потоку даних нейронів: у новому нейроні дані успадковуються, переробляються та надходять у наступні нейронні процеси тощо. У більш широкому сенсі, творчість неминуча в процесах ШНМ, оскільки якщо швидкість навчання занадто велика, збіжність функції помилки більше не гарантується; якщо швидкість занадто мала, кількість необхідних тренувальних пробіжок може стати дуже великою. Під час коригування ваг може статися так, що оптимізація застрягне в локальному мінімумі.

Ключові слова: *штучні нейронні мережі, Вайтгед, коннекціонізм.*

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