

Algorithmic Self-Instructing Consciousness

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ABSTRACT

Let us be outgoing from the thesis: if consciousness corresponds to the capacity to integrate information, then the system should be able to generate consciousness to the extent having a large repertoire of available states (information). Natural selection is an algorithm for generating adaptation and the question is, whether it may be utilized for cognition. Natural selection is capable to improve itself as a heuristic search algorithm. In neuronal information self-transfer is possible formation of a one-to-one topographic map between two neuronal layers, and reconstruction of the intra-layer topology of the parent in the offspring layer. The problem of neuronal transfer exists, from anatomical (activity-dependent) mechanisms, to self-instructing (activity-independent) algorithms. We establish a link between network topology and information integration showing how biologically inspired auto-adaptation improves the consciousness self-instructing.

Key Words: algorithm, auto-adaptation, self-organization, consciousness, integrated information theory

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Introduction

Units of selection include units of life such as organisms and lymphocytes evolving by somatic selection. Also purely informational entities like viruses, machine code programs and binary strings in a *genetic algorithm*. Natural selection is an *algorithm for generating adaptation* and the question is, whether it may be utilized for *cognition*. Natural selection is capable to improve itself as a *heuristic search algorithm*. In organismic biology there is various systems for inheritance based on metabolic networks, on conventional genes and *epigenetic mechanisms*. In *neuronal information self-transfer* is possible formation of a one-to-one topographic map between two neuronal layers, and reconstruction

of the intra-layer *topology* of the parent in the offspring layer. The problem of *neuronal transfer* exists, from anatomical (activity-dependent) mechanisms, to *self-instructing* (activity-independent) *algorithms*.

By utilizing Hebbian learning with Oja's synaptic renormalization rule in the between-layer connections, using lateral inhibition in the child layer (*soft-competition*) is possible to *self-organize* a topographic map between layers. During reciprocal interference mechanism A mistakenly interprets the neurons as independent of each other, when in-fact they *mutually cause* each other to fire.

Materials and Methods

If examine two error correction mechanisms that compare the phenotypes of the networks, i.e. the spike-timing, and make direct changes to the genotypes, it means change in the underlying *topologies*. This is in contrast to error correction

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in DNA replication where only the genotype is checked for errors.

The neighborhood function has the most central role in *self-instructing*. In biological modeling it seems best materialized by *the diffusion* of some chemical control agents from places where the cell activity is high.

Defining the recursive step is first the input data item $x(t)$ selects the best matching model in the grid. The model of this node and its *spatial neighbors* in the grid is modified. The rates of modifications at different nodes depend on the mathematical form of the function $h_{ci}(t)$. A much applied choice for *the neighborhood function* $h_{ci}(t)$ is

$$h_{ci}(t) = \alpha(t) \exp[-sqdist(c,i) / 2\sigma^2(t)],$$

where $\alpha(t)$ is a monotonically (e.g. hyperbolically, exponentially or *piecewise linearly*) decreasing scalar function of t , $sqdist(c, i)$ is the square of the geometric distance between the nodes c and i in the grid, and $\sigma(t)$ is another monotonically decreasing function of t , respectively. The final value of σ shall not go to zero, because otherwise the process loses its *ordering power* (Kohonen, 2013).

Above modeling approaches are successful theoretical proofs of *input-driven self-instructing*. In them, the emergence of feature-sensitive cells is involved in the so-called *competitively learning neural networks*. In a subset of cells, *adaptation* of strongest-activated cells to the afferent input signals made them tuned to the specific input features or their combinations.

Sparse activity in the excitatory neurons of layer 2/3 or layer 5 of *the somatosensory cortex* results in the recruitment of a recurrent inhibitory circuit with inhibitory interneurons that are somatostatin positive. Through this mechanism, one pyramidal cell can inhibit about 40% of its neighbours. If two pyramidal cells are spiking the resultant recurrent inhibition increases *nonlinearly* as a result is tenfold increase in the recruitment of the inhibitory interneurons which receive convergent inputs.

Such a circuit limits activity spreading in the horizontal layers, preventing reverberation, while the principal neuron continues to *integrate information* and *convey* it to the next processing region. A circuit with similar properties occurs in *the hippocampus* (Fernando *et al.*, 2008).

Information integration in the brain

Processing in the brain is competitive, but not only competitive. Different pathways, carrying different sources of information, compete for expression in behavior, and the winners are those with *the strongest sources of support*. Competition is just one aspect of natural selection. *Heuristic search* may be *an algorithm* that underlies all the *cognitive functions*. The possible sites of *the information integration* are the loops between *medial temporal cortex* (including *the hippocampus*) and *the neocortex*. Temporal correlation of the source and recipient neuronal assemblies is a prerequisite for *information transfer*.

But we mean *the reciprocal information transfer* in contrast to the unilateral and passive information-transfer process. The loops between the medial temporal cortex (containing the hippocampus) and the neocortex are implicated in memory consolidation and reconsolidation, processes that involve *gradual reorganization* of circuits. *The integrative function of the hippocampus* is taken over by *the medial prefrontal cortex* at least for semantic memories. *The anterior cingulate cortex* is involved in the remote memory for contextual *fear* (Franklin *et al.*, 2008; Dias & Ressler, 2014) conditioning as a hippocampus-dependent task.

Evidence for this theory has been found using the horizontal opto-kinetic response (HOKR). The memory for the HOKR is "shunted" (Grossberg, 1976) transynaptically from the cerebellar cortex to the inferior olivary nucleus. A functional memory trace is formed initially within the parallel fiber-Purkinje cell synapse of the cerebellar cortex (flocculus) by an LTD mediated mechanism and later *shunted* to the vestibular nuclei (medial vestibular nucleus). There it appears to be consolidated into a long-term memory trace (Kohonen, 2013).

Later there was introduced a new *self-instructing system model* related to the Self-Organizing Map (SOM) *algorithm* with a *linear transfer function* for patterns and combinations of patterns all the time. It started from a randomly interconnected pair of neural layers, and using random mixtures of patterns, which creates a *pointwise-ordered projection* from the input layer to the output layer. When the input layer consists of feature detectors, the output layer forms a *feature map* of the inputs.



The essence of two separate functions, the winner-take-all (WTA) and the neighborhood function, is incorporated into the mathematical SOM algorithm. The SOM is using two different kinds of signaling variables: the neural signals themselves, and the plasticity-control information (possibly chemical). The later modifies the synapses but does not participate in the signal transfer itself.

Another influential modification of the law of Hebb is to replace the postsynaptic activity by a combined control effect of the active neighboring neurons. In a similar sense as the neighborhood function was defined in the earlier biological SOM algorithms, a laterally spreading plasticity-control agent (possibly chemical) is assumed (Kohonen, 2006).

Learning should be confined due best-matching (strongest) synapses, e.g. by making the learning proportional to the synaptic strength. If the plasticity law is modified, learning will mainly be confined to those synapses that are most decisive in matching. This modification will organize the neural projections effectively. Let $w_{ij}(t)$ be the strength of the synaptic connection from input neuron j to output neuron i at time t . The postsynaptic activity in the law of Hebb will be replaced by the combined effect $u_i(t)$ that depends on the activities of the neighboring neurons. The organizing results may also depend on the initialization of the weights and input data sequence: for the self-instructing criticality.

Autoadaptation of neural to psychological code

Experimental information on the organization of brain comes from observation of power laws $1/f^\alpha$ with $\alpha \approx 1$ in the frequency power spectrum of electrical signals measured by electroencephalograms (EEG). Such power laws reflect a fractal temporal behavior. Power laws in frequency have been observed in local field potential (LFP).

We can establish a link between network topology and flow of information to show that biologically inspired autoadaptation may lead to conversion of the neural code to psychological code.

To each neuron is given weight vector w_i in the same vector space as the stimuli, at each time

t , a stimulus p_q , is randomly selected, and the neuronal weights are updated according to rule of Hebbian learning: $w_i(t+1) = w_i(t) + \eta(t) (p_q(t) - w_i(t))$, $\forall i \in V_g(t)$, where neuron g is the winning neuron, closest to stimulus p_q , and V_g defines an order of neighborhood (topology) for neuron g .

The parameter η denotes the learning rate. The order of neighborhood $V(t)$ is initially high, i.e. the map is highly connected. During the evolution of organization $V(t)$ decreases gradually, and $\eta(t)$ decreases linearly to ensure convergence of neuronal weights.

A locally independent learning rate can be formulated as the function of local attraction $A_i^{int}(t) = A_i^{int}(t-1) + \delta_{i,g(t)} \|p_q(t) - w_i(t)\|$ for $i = 1, \dots, n$. From local attraction we construct an adapted learning rate individually different for each neuron $\eta_i(t)$.

Starting from such new learning rate, we define an internal knowledge function K^{int} , expressed in terms of a harmonic mean

$$K^{int}(t) = \frac{n}{\frac{\sum_i^n \bar{A}^{int}(t) \oplus A^{int}_i(t)}{\bar{A}^{int}(t)}}$$

with initial value $K^{int}(0) = 0$, where \bar{A}^{int} denotes the average of A_i^{int} over all neurons $i \in \{1, \dots, n\}$, the decreasing error function E^{ext} mirrors the behavior of function K^{int} and justifies the interpretation of the latter as knowledge gain. The change of the topology adapts itself to the rhythm of knowledge gain (Pallaver et al., 2006).

In information theory the network connectivity dimensions are defined on global and local scale, D_{glob} and D_{loc} , which explicitly show the link between topology and function of the network, and here means effective transfer of information during conversion of neural to psychological code. In neurobiology, often there is a link between structure and function, which corresponds to the regime of accumulated (learnt) knowledge, i. e. to the psychological code. Mapping (reducing) the high-dimensional manifold of Q stimuli to a low-dimensional (2-D)



manifold maintain *topological continuity*, i.e. proximate stimuli activate proximate neurons.

New studies have hinted that *transfer of environmental factors* can influence biology more rapidly through *epigenetic modifications*, which alter the expression of genes, but *not their nucleotide sequence*. Epigenetic modifications are known in development and the activation of *one copy of the x-chromosome* in females. The latest study about *epigenetic inheritance* showed that there's also *intergenerational transfer* of risk, and that it's hard to break this cycle (Dias & Ressler, 2014). Similar experiments showed that *the response* can also be *transmitted* down from the mother.

These responses were paired with changes to the brain structures (that process odours). The mice sensitized, as well as their descendants, had more neurons that produce a receptor protein (detecting the odour). Structures that receive signals from the detecting-neurons and send (smell) signals to the other parts of the brain (processing fear) were also bigger. *DNA methylation* (a reversible chemical modification to DNA that *blocks transcription* of a gene) *without altering its sequence* explains the inherited effect. In the fearful mice, *the sensing gene of sperm cells* had a fewer *methylation marks*, which lead to greater expression of the (odorant) receptor gene.

Sperm cells themselves express odorant receptor proteins, and they find the way into the bloodstream, offering a *potential mechanism*, as do blood-borne fragments of RNA known as microRNAs, that control gene expression. Our germ cells are so plastic and dynamic in response to changes in the environment. Humans inherit epigenetic alterations that influence behavior by *self-instructing* too. A parent's anxiety could influence *transfer* to later generations through *epigenetic modifications to receptor for stress hormones* (Dias & Ressler, 2014).

Conclusions

In the biological realms, genetic information already defines *initial order* of the neural projections. Refinement of this order continues prenatally, by endogenous signals generated by *the self-instructing network itself*. *The final resolution* of the mapping and optimization of the neural resources are achieved postnatally, by *sensory experiences (epigenetically)*. The exposure

of infant rats to complex tone sequences results in *altered organization* of the auditory cortex. These evidences prove that *the input-driven organization* of typical brain maps is a fact and needs a new *epigenetic model of self-instructing consciousness*.

A modification of the signal-transfer law has also an *automatic standardization effect* on the synaptic strengths ordering, called "*shunting*" (Grossberg, 1976, Kohonen, 2006).

The evidence for a *neighborhood control of the synaptic plasticity* comes from the observations: theoretical, physiological, and behavioral. The well-known plasticity-controlling *neuromodulators* like *noradrenaline* spread diffusely across *the cerebral cortex*.

It is plausible that the local neural signals are able *self-instructing* the receptors of neuromodulators, enhancing the plasticity-control effects locally or restricting them to the neighborhoods of the signal activities. The plasticity-control effects may be mediated also by anatomical structures like *the interneurons* and their nonsynaptic *control* actions.

Traumatic experiences in early life can persist through adulthood and have often been *transmitted across generations*. Chronic and unpredictable maternal separation also *alters the profile of DNA methylation in the promoter* of genes in the germline of the separated males. Similarly changes in DNA methylation are also *present in the brain of the offspring* and are associated with *altered gene expression* (Franklin *et al.*, 2010).

These findings highlight the negative impact of early *stress* on behavioral responses across generations and on the regulation of *DNA methylation in the germline*. *The environmental information* may be inherited *transgenerationally* at behavioral, neuroanatomical and *epigenetic* levels.

Consciousness exists and is *observer-independent*, says information-integration theory (IIT). It is both *integrated* (each experience is unified) and *informative* (each experience is defined by its differing). IIT produces a novel, *non-Shannonian* integrated information, measured as difference to a system from its *intrinsic perspective*, not relative to an observer (Tononi, 2008). This novel definition of information helps to quantifying and

characterizing consciousness as *self-instructing by brains* and in the future *by machines*.

One of the central notions of *self-instructing* is exactly this: only *local maxima of integrated information exist*. My consciousness, your consciousness, but *nothing in between*, no superordinate consciousness. *Self-instructing* is based on the constructive, predictive *mathematical algorithms*.

We experience consciousness when we *integrate* different sensory inputs. *Phi* is a measure of the extent to which a given system (a brain circuit) is capable of *self-instructing* distinctive bits of information. The more distinctive the information, and the more specialized, integrated the system is, the higher

its Φ (*Phi*) directly measures consciousness, *the higher your phi, the more conscious you are*.

Creatures like dogs, mice and cats might have some degree of awareness (though less than humans). Anything with *phi* greater than zero possesses at least a *shred* of consciousness. By that definition, many organisms, and even some computers, *are conscious* by virtue of the ways they *algorithmically self-instructing information*.

The value reflects how much *information a system's mechanisms self-instructing above and beyond its parts*. *Phi* is actually a barometer of *intelligence and consciousness*. *Phi*- clearly gives us a *new way to think* about *self-instructing* between *information* and *consciousness*.

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