Algorithmic Self-Instructing Consciousness

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ABSTRACT
Let we are 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...
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

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

where $\alpha(t)$ is a monotonically (e.g. hyperbolically, exponentially or piecewise linearly) decreasing scalar function of $t$, $\text{sqdist}(c,i)$ 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 $\sigma$ 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 somatostatine 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 cingulated 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 (floculus) 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 form 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).

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: $w_i(t+1) = w_i(t) + \eta(t) \left( p_q(t) - w_i(t) \right), \forall i \in V_g(t)$, 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 $\eta$ 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 $A^\text{int}_i(t) = A^\text{int}_i(t-1) + \delta_{i,g(t)} \|p_q(t)-w_i(t)\|$ for $i = 1,\ldots, n$. 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 $K^\text{int}$, expressed in terms of a harmonic mean

$$K^\text{int}(t) = \frac{n}{\bar{A}^\text{int}(t)} \sum_{i=1}^{n} \bar{A}^\text{int}(t) \oplus A^\text{int}_i(t)$$

with initial value $K^\text{int}(0) = 0$, where $\bar{A}^\text{int}$ denotes the average of $A^\text{int}_i$ over all neurons $i \in \{1,\ldots,n\}$, the decreasing error function $E^\text{ext}$ mirrors the behavior of function $K^\text{int}$ 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, $D^\text{glob}$ and $D^\text{loc}$, 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 phi. \( \Phi \) (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.

References