Modular Neurocomputation with Artificial Gravisensory Neural Systems: An Ontogenetic Perspective

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Abstract

Biomimetic computation seeks to develop artificial intelligence by methodologies inspired by natural information processing mechanisms. Genetic algorithms simulate biological evolution by operating on genotypes, while evolution strategies and evolutionary programming emphasize phenotypes. However, the ontogenetic mapping of genotypic space to phenotypic space in biological systems is not deterministic, because ontogenesis is influenced by epigenetic factors, acting at the microenvironment and macroenvironment levels. Hence, phenotype results from both genetic and epigenetic operators. Although genomes and phenomes are fundamental aspects of evolutionary theory, ontogenetic evolutionism requires integration into the neoDarwinian synthesis, and epigenetic operators should be included in evolutionary computation. In this context we propose a novel perspective for simulated evolution: ontogenetic programming, in which ontogenetic algorithms involving epigenetic operators shape the adaptive trajectories of massively parallel cellular tensor multidimensional manifolds during somatic development. We outline its theoretical rationale and its modular application to neurocomputational biocognitronics models, artificial life, and evolvable neuromorphic hardware.

Introduction: Biomimetic Computation

The creation of artificial intelligence and artificial life has been a goal of mankind from the beginnings of recorded history, as exemplified by Homer's account of Hephaistos' automata in *The Iliad*. Even the earliest computer scientists focused on biological systems for inspiration in their computational endeavors. Alan Turing (Hodges 1983) thought about the operation of assemblies of nerve cells in his quest to understand how brains learn, and became interested in biological pattern creation by means of morphogenesis. John Von Neumann (Aspray 1990) considered that the central nervous system employs a primary language from which mathematics is derived. And Norbert Wiener's seminal work *Cybernetics* (Wiener 1961) is actually subtitled "control and communication in the animal and the machine".

More recently several computational approaches inspired by biological processes have been developed; they form part of a field that we call *biomimetic computation*. For instance, artificial neural network models are algorithms based on the structure of biological nervous systems which are used for cognitive tasks such as learning and optimization. Cellular automata represent prototypical models for complex processes consisting of numerous identical, simple, locally connected elements with computational capabilities which provide insights into the behavior of extended dynamical systems, and are inspired by the geometrical organization of biological cells in tissues. In addition, the efficiency of neoDarwinian evolution as a search and optimization problem-solving mechanism has led to the elaboration of various paradigms that seek to create artificial intelligence by simulating natural evolutionary processes. However, there are other bioinformatics approaches that instead of simulating biological processes, actually employ biological macromolecular substrata, as in the case of DNA computing (Adleman 1994).

Evolution of Intelligence or Intelligence of Evolution?

The human brain is the most complex neurocomputational biological machine produced by natural evolution. And yet it is the intelligence of evolutionary mechanisms which has resulted in massively parallel biological optimizations to natural problems over eons. The engineering problem of addressing increasing complexity has been approached by biomimetic computational paradigms that simulate the evolutionary process. In contrast to expert systems used in knowledge engineering, these distributed problem-solving approaches seek to simulate nature's evolutionary mechanisms as described by the neoDarwinian synthesis, affording an effective strategy in situations where complex information processing systems require adaptive responses to a changing environment. Even Turing described a parallel between intelligence and "the genetical or evolutionary search by which a combination of genes is looked for", stating that "the remarkable success of this search confirms to some extent the idea that intellectual activity consists mainly of various kinds of search" (Hodges 1983). He envisioned evolutionary computation as a program that would simulate the plasticity of a child's mind instead of an adult's, thus affording a wider repertoire of choices as it grows. This viewpoint represents *artificial* or *synthetic ontogenesis*, and is based on a biological perspective that we call *developmental evolutionism* or *somatic neoDarwinism*. In contrast, widely used paradigms in evolutionary computation focus on the genotypic or phenotypic levels, excluding the ontogenetic process.

Genetic, Ontogenetic, Phenotypic Evolutionism

Well described evolutionary computational approaches can be divided into two major categories, depending on level of abstraction (genotypic or phenotypic). Genetic algorithms and genetic programming focus on genotypic transformations, while evolutionary programming and evolution strategies emphasize phenotypes (Fogel 1995; Back, Hammel, and Schwefel 1997).

The concept of genetic algorithms (Holland 1992), introduced and developed by John Holland and his collaborators, is based on formulating any problem in adaptation in genetic terms. Genetic algorithms transform a "population" of individual mathematical objects into a new population. The objects in the original set are patterned after "chromosomal" strings with associated "fitness" values, which are transformed into the next "generation" by means of operations based on neoDarwinian principles such as reproduction and survival of the fittest, as well as other naturally occurring genetic mechanisms like recombination. The genetic programming paradigm increases the complexity of the structures undergoing adaptation by employing general hierarchical computer programs of varying characteristics.

In contrast to the bottom-up approach used by the aforementioned genetic strategies, evolutionary programming and evolution strategies are optimization tools that focus from the top-down, phenotypic level. For instance, evolutionary programming emphasizes the linkage between "parents" and their "offspring" instead of emulating specific genetic operators, and is devoid of the representational constraints of genomic string encoding.

However, in biological systems, the ontogenetic mapping of genotypic state space to phenotypic state space is not deterministic, exhibiting irregular trajectories that may even result in regressive developmental events such as somatic cell death (Figure 1). This is because the process of ontogenesis is influenced by epigenetic factors, which act at the microenvironment (e.g. epistatic effects) and macroenvironment (e.g. gravitational forces) levels. Hence, phenotype results from a combination of both genetic and epigenetic operators during ontogenesis. Nonetheless, although the genomic and phenomic levels represent fundamental aspects of current evolutionary theory, developmental evolutionism requires further integration into the neoDarwinian synthesis, and epigenetic operators need to be included as part of evolutionary computational paradigms. In this context we propose a novel paradigm for simulated evolution: *ontogenetic programming* (OP). OP employs *ontogenetic algorithms* (OAs) involving *epigenetic operators* (EOs) which shape the trajectories of massively parallel cellular tensor manifolds (denoting differential gene expression in multidimensional space) on adaptive landscapes during somatic development. This paradigm is partly based on the theoretical underpinnings of ontogenetic evolvability, developmental statistical mechanics (*ontogenetic mechanics*), topobiology, and neuronal group selection theory, as well as on our investigations of epigenetic effects on cellular differentiation and morphogenesis, such as the induction of DNA rearrangements (McCarty and Love 1989), cellular tensegrity (Love and Johnson 1999a), and biological neural network topohistogenesis (Love and Cohen 1990; Cohen and Love 1993).

It is important to note that some investigators, not formally trained in biological sciences, have attempted to address developmental issues (e.g. Sipper et al. 1997, Nolfi et al. 1994, Cecconi el al. 1995, Gruau and Quatramaran 1997). However, they have generally focused on learning and behavior, considered the process predominantly deterministic, and given the biological terminology interpretations that differ significantly from the phenomenology exhibited by natural organisms.

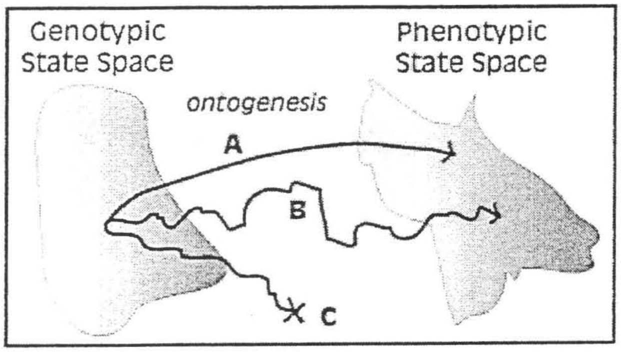

Fig. 1. Lewontin-type diagram illustrating the mapping of genotypic state space to phenotypic state space. The ontogenetic process is not deterministic (*A*), but rather a sinuous trajectory (*B*) shaped by epigenetic factors, which can result in regressive developmental events such as somatic cell death (*C*).

Theoretical Framework for Somatic neoDarwinism

The concept of relating the somatic developmental process (ontogeny) to the evolutionary hierarchy of animal species (phylogeny) is not new (Depew and Weber 1995). Darwin realized that an understanding of embryology was essential to comprehend natural selection. Haeckel, who coined the terms "ontogeny" and "philogeny", considered that embryonic development was simply an accelerated version of evolution. His "biogenetic law" postulated that life histories of organisms recapitulate their evolutionary histories, and is based on the study of the similarities between early embryos of various species (Figure 2). This inaccurate view was thereafter rejected by other developmental biologists like Roux, who emphasized a causal view of embryogenesis, proposing a scheme that he called "developmental mechanics" (in analogy to Newton's laws of celestial mechanics). Nonetheless, it is possible to consider the developmental process under the evolutionary viewpoint, but at the cellular level. The following theoretical approaches, emphasizing an ontogenetic framework for natural evolution, have recently contributed to the foundations of developmental evolutionism (somatic neoDarwinism), which represents the biological basis for ontogenetic programming.

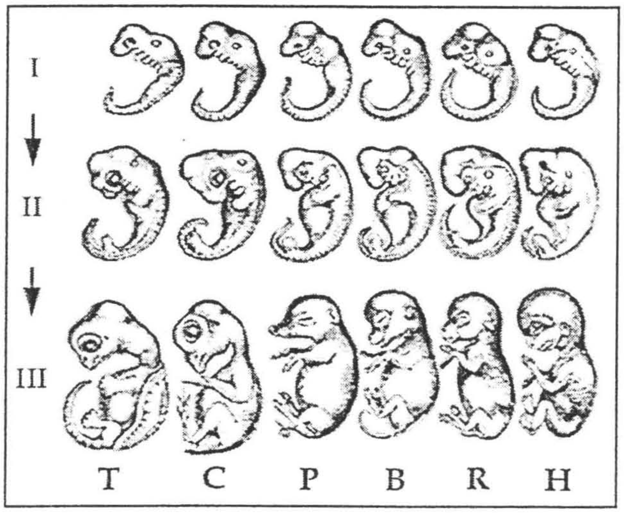

Fig. 2. Morphological similarities of vertebrate embryos at various stages of development (after Romanes 1901), a fundamental observation suggesting common phylogeny and similar basic morphogenetic mechanisms (T=tortoise, C=chick, P=pig, B=bovine, R=rabbit, H=human).

Statistical Mechanics of Development and Ontogenetic Evolvability

Lewontin's analysis of the evolutionary process denotes that a theory of genotype to phenotype mapping (ontogenesis) is essential in order to complete the neoDarwinian synthesis. In this context, Kauffman (Kauffman 1993, 1994) has reported the need for a new statistical mechanics (developmental mechanics), in which the "developmental program" encoded by DNA can be viewed as a parallel-processing genomic system whose dynamical behavior unfolds during ontogeny. According to this framework, cell differentiation can be interpreted as a parallel-processing expression of genes in each cell lineage. Thus, it is necessary to understand how a biological organism arises from a parallel-processing dynamical system, and is molded by evolution and selection, in order to comprehend embryonic development from the fertilized zygote, and the evolvability of ontogenesis.

Kauffman's "cell differentiation Boolean dynamical network" models the cybernetic genetic regulatory network underlying cell differentiation and ontogeny. This theoretical framework uses concepts from Boltzmann's statistical physics and dynamical systems theory, describing the relation between self-organization and selection. Adaptive evolution is modeled as a rugged "fitness" landscape, and alternative cell types are represented as state cycle dynamical attractors in genomic architecture space, where recurrent patterns of gene activity converge asymptotically (Figure 3). Hence, number of attractors map to cell type number, size of attractors map to gene expression pattern restrictions, and evolution of novel cell types results from alterations of attractors (as by means of mutation). Cell types are specified by a combinatorial epigenetic code. Adaptation occurs at the boundary of chaos, optimizing evolvability.

In addition to the cellular differentiation issue (addressed above), the main problem in ontogeny is morphogenesis, the process by which cells become coordinated into organized tissues and organs. Kauffman approaches morphogenesis by means of an ensemble theory, integrating combinations of developmental mechanisms. Thus, pattern formation can be analyzed by cellular positional information in topological maps. In this framework, basins of dynamical attraction and cellular typology can be modified during development by mechanochemically modeled vectorial effects, such as "microhormone" gradients. In contrast to their genomic counterparts, morphologic fitness landscapes can be smooth in addition to rugged. In sum, by achieving self-organization at the edge of chaos, selection optimizes the capacity of genomic systems to perform complex gene-coordination tasks and evolve effectively, achieving optimal morphogenesis.

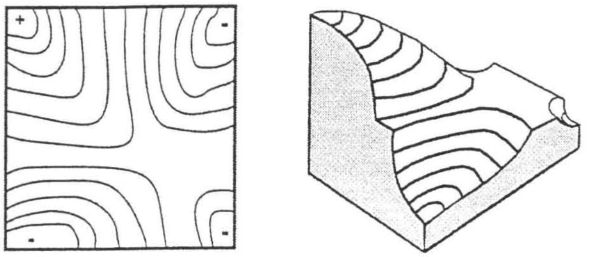

Fig. 3. Statistical mechanics inspired rugged fitness landscape (*top and lateral views*). During the ontogenetic process, developing cells adapt to a varying genomic and morphologic topography shaped by epigenetic factors, following (evolving) developmental trajectories in somatic time toward optimized phenotypes (dynamical attractors, denoted by landscape peaks).

Developmental Topobiology and Neuronal Group Selection Theory

Edelman (Edelman 1987, 1988) has stressed that the ontogenetic mapping of genotypes to phenotypes represents the most important of all evolutionary problems, without which the modern synthesis is incomplete. He has approached this issue within the topobiological framework. Topobiology focuses on place-dependent intercellular interactions that lead to the regulation of the primary processes of embryonic development and morphologic evolution. Topobiological mechanisms link developmental genetics to mechanochemical events, taking into account epigenetic factors, whose understanding is essential to complete the picture of molecular embryology. Environmental (epigenetic) factors, both internal and external, can exert a great selective force on newly appearing genetic changes. Hence, during development, epigenesis is just as important as genetics. While ontogenesis has genetic underpinnings, developmental events are epigenetic and topobiologically controlled. Thus, development involves highly nonlinear epigenetic changes, which are highly context dependent. Pattern, not simply cell differentiation, is the evolutionary basis of morphogenesis.

Edelman's "morphoregulator hypothesis" is based on the notion of development as not being simply or directly related to genetic change. Instead, the primary processes that drive development show stochastic and nonlinear interactions that depend on mechanochemical factors, which are not prefigured in genes. Moreover, there are topobiological constraints upon the size, movement, and interaction of cell assemblies. The temporally regulated expression of morphoregulators provides the selectivity that guides and kinetically constrains primary morphogenetic processes. Functional adaptive diversity and phenotypic variability result from the interaction of both genetic and epigenetic factors during development.

Edelman's "neuronal group selection theory" (neural Darwinism) uses population thinking to evaluate nerve cells during neural development, and focuses on the adaptive aspect of variation and selection in brain connectivity reentrant mappings and signal patterns. Thus, the Darwinian aspect of cognition appears not only in its phylogenetic evolution but also in its somatic selectional processes. Although operating by means of different mechanisms, the immune system is also capable of intelligent recognition and exhibits somatic evolution.

Epigenetic Factors Affecting Differentiation and Morphogenesis: Case Studies

The theoretical frameworks outlined above (ontogenetic evolvavility, developmental statistical mechanics, topobiology, and neural Darwinism) emphasize the importance of including the epigenetic perspective (in addition to the genetic) when analyzing the appearance of phenotypes by means of the ontogenetic process (somatic evolution). The following examples serve as illustrations of the effect of epigenetic influences on morphogenesis and differentiation in biological systems.

Gravimorphogenesis and Sensory Deprivation

Epigenetic stimulation is essential to development of various sensorineural systems. For instance, in the visual system, partial or total deprivation of visual stimulus during a critical developmental period results in irreversible abnormalities of the retina and several neural elements involved in the processing of visual information. We are investigating the molecular and cellular underpinnings of gravisensory mechanisms in plants and animals, both under terrestrial conditions and in the spaceflight environment (Love and Cohen 1990; Johnson and Love 1999). The force of one gravitational unit characteristic of terrestrial ecosystems represents a stable and pervasive epigenetic influence that has affected the development of biological organisms on the surface of planet Earth throught evolution. The effect of alterations of this epigenetic agent in the near-weightlessness (microgravity) medium of space are not well understood, and may contribute to fields ranging from gravitational biology to neurovestibular pathophysiology.

Gene Amplification and Topological DNA Rearrangements

Many topological rearrangements of the genetic material are epigenetic in origin. For instance, we have studied DNA alterations in cultured cells that became resistant to heavy metals, and described a gene amplification phenomenology (McCarty and Love 1989). In this case, the epigenetic influence of high concentrations of heavy metals (such as cadmium) resulted in amplification of the genes coding for metallothionein, a protein involved in heavy metal detoxification and homeostasis. Anticancer platinum-based drugs were also shown to cause this type of DNA rearrangement. Gene amplification plays an important role in evolution, affording the template for the generation of multigene families as well as gene products with related structural and functional domains.

Embryonic Induction and Cellular Tensegrity

Embryonic induction represents an epigenetic mechanism described by early experimental embryologists. For example, in amphibians, formation of the eye's lens is induced in the ectoderm overlying the optic vesicle. Removal of the optic vesicle results in failure of the lens to develop; conversely, transplantation to another part of the organism results in lens induction in the overlying ectoderm. More dramatically, inter-species transplantation of mesoderm also induces region-specific differentiation of ectoderm which then expresses its cell lineage fate according to its origin.

Cellular tensional integrity (tensegrity) is another epigenetic aspect involved in ontogenesis (Love and Johnson 1999a). Mechanical forces transmitted via the cytoskeletal network can modify the subcellular geometry of enzymes, thus influencing biochemical reactions and the differential gene expression they control. Moreover, cellular tensegrity helps explain self-assembly mechanisms essential to morphogenesis.

Apoptosis, Trophism, and Regressive Ontogenetic Mechanisms

The epigenetic effect of chemical agents in the ontogenetic process has a long history. Turing's interest in embryology led him to propose a chemical hypothesis for onset of pattern in dissipative systems (Hodges 1983). We have investigated spatiotemporal aspects of the development of the avian statoacoustic ganglion (Love and Cohen 1990; Cohen and Love 1993), a system in which some 25% of neurons die during ontogenesis (Figure 4). This regressive ontogenetic event is important in the development of the mature vertebrate nervous system. Programmed cell death (apoptosis) has been shown to occur in certain systems in the absence of a trophic factor, such as nerve growth factor in the case of sympathetic neurons (Johnson and Deckwerth 1993).

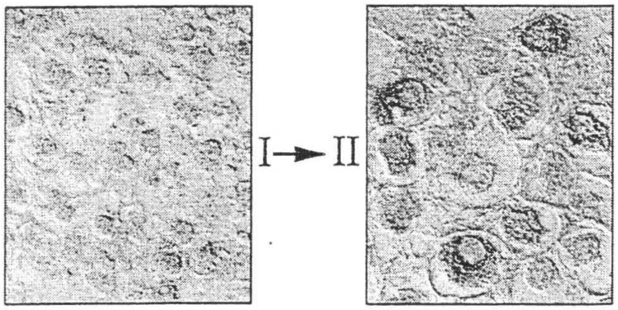

Fig. 4. Morphological and biochemical changes in neuronal cell bodies (perikarya) during the ontogenesis of the avian statoacoustic ganglion. As neuronal cells develop *(from I to II)*, they exhibit variation in sizes, as well as in neuron-specific enolase and neurofilament protein 200 kD immunoreactivities. Epigenetically regulated developmental cell death accounts for their reduction in number during embryogenesis.

Toward Artificial Ontogenesis: From Adaptive Biomimetic Models to Evolvable Biomorphic Hardware

Ontogenetic programming is being developed as a dual purpose tool: to evolve/adapt reverse engineered symbolic biomimetic models, and as a basis for *ontogenetic engineering* of adaptive/evolvable biomorphic machines.

For instance, we are interested in generating adaptive/evolvable gravisensory systems modeled after their biological counterparts by means of *biocognitronics* (BCT) reverse engineering (Love and Johnson 1999b). The BCT hybrid approach produces neurocomputational symbolic abstractions by implementing methodologies that combine fuzzy logic, cellular nonlinear automata, and artificial neural network elements in addition to the tools of statistical mechanics, tensor calculus, complexity, and dynamical systems theory. Applying BCT techniques to the vertebrate gravity-sensing organs (VGSOs) has yielded a protypical artificial gravity-sensing organ (AGSO): GRAVICOGNITOR (GC). GC is based on the cellular geometry and dynamic connectivity of VGSOs, and in its preliminary version exhibits the following pattern recognition characteristics. The gravitoinertial tensor space input on the otoconial membrane (depicted as a matrix with viscoelastic and piezoelectric properties) is converted to an Ising-like fuzzy encoding lattice (representing the directional sensitivity of apical sensory hair bundles) by means of coordinate transformations. The resulting fuzzy electrotonic functional polarization patterns are then mapped to a manifold of hypercubical nonlinear fuzzy cytodes (representing the neuroepithelium), which are linked to a cellular nonlinear network of multidimensional fuzzy neurodes (representing the canonical nerve cell bodies in the first order sensory ganglion) interconnected by means of reentrant pathways. In this manner, the computational mechanics of gravicognitive pattern recognition are described by means of sequential mapping functions that transform gravitoinertial state space into sensorineural state space. GC can evolve by means of ontogenetic programming, and is the basis for related pattern recognition adaptive/evolvable modular hardware.

Artificial Life Implications and Concluding Remarks

During a recent conference on evolvable hardware, when the question was asked about expectations for the field by the year 2008, one of the panelists stated that more attention should be placed on "the transfer from genotype to phenotype" (DeGaris 1998). This perspective also applies to the field of artificial life in general, and is the focus of our ontogenetic ideology, which emphasizes the aspect of evolutionary theory without which the neoDarwinian synthesis remains incomplete. Ontogenetic programming with epigenetic operators may contribute to a more realistic modeling of adaptive/evolvable neurocomputational systems, as in the case of our artificial gravity-sensing organ. By simulating somatic neo-Darwinism, it fills the gap between the genotypic and

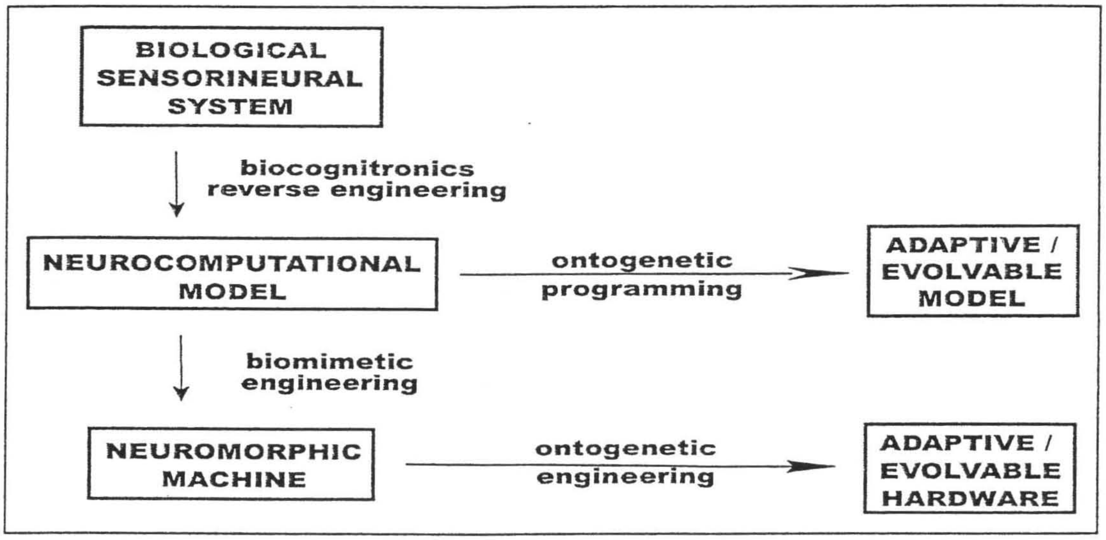

Fig. 5. Relationships between biologically-inspired artificial systems and biomimetic paradigms based on developmental evolutionism (somatic neoDarwinism).

phenotypic levels not addressed by other evolutionary computational paradigms; this is essential for artificial morphogenesis. Moreover, it may be used in the design, development, and control of adaptive/evolvable hardware by means of ontogenetic engineering. For instance, the biological neural net in our model of the vertebrate gravisensory apparatus can be used as a prototypical module in the generation of biomorphic cognitive machines that can adapt/evolve, as well as in other bioelectronic hardware. In conclusion, the following chart summarizes the relationships between biomimetic approaches based on developmental evolutionism and various biologically-inspired synthetic systems (Figure 5).

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