General Theory of Intelligent Relativity: An Intelligence Model Based on the Matching Degree between Potential Field Structure and Problem Constraints

Abstract

This paper, based on the Dynamic Generative Theory and the *Special Theory of Intelligent Relativity*, proposes the **General Theory of Intelligent Relativity**. This theory posits that the cognitive difficulty of a problem is not its inherent attribute, but rather an emergent result of the **compatibility between the problem's constraint sequence and the solver's individual potential field structure**. Intelligence is redefined as a **relational, domain-specific quantity** that can be quantified by *Generative Complexity.* To circumvent the extreme complexity of real cognitive agents' historical imprints, this paper constructs a thought experiment based on the *"baby counting candies"* task. By quantifying the matching degree between different simplified potential fields and the same problem constraints, it demonstrates how the Generative Complexity (G) varies across agents. The model proves that the traditional concepts of *objective difficulty* and *universal intelligence* are misleading products of the static paradigm; the essence of intelligence is the **dynamic resonance between the coherent structure formed by the potential field in historical practice and the constraints of the present problem**.

Keywords: General Theory of Intelligent Relativity; Generative Complexity; Potential Field; Matching Degree; Coherent Structure; Cognitive Dynamics; Individual Differences

1. Introduction: From Absolute Difficulty to Relative Compatibility

In *The Generative Dynamics Foundation of Computational Complexity* and the *Special Theory of Intelligent Relativity*, we established a formal framework centered on **solution space compression**, defining the generative complexity $G(P)$ of a problem for a **blank cognitive agent** (historical depth H=0). This measure successfully anchored difficulty in the constraint dynamics of the problem itself.

However, real cognitive agents—humans—are not blank. Each individual possesses a **potential field** Ψ_S deeply shaped by their unique life history (education, culture, practice, experience), containing intricate networks of concepts and associative structures. This raises a fundamental question: **Does the same problem P have the same difficulty for different agents S?**

Traditional theories of intelligence (e.g., the g-factor theory) implicitly answer affirmatively, viewing intelligence as an intrinsic, universal property of the agent, where difficult problems are equally hard for everyone, and the advantage of the intelligent lies in their stronger "general processing power".

The General Theory of Intelligent Relativity completely overturns this picture. It posits: **Difficulty emerges from the encounter between the agent and the problem.** The generative complexity $G(P, S)$ for agent S to solve P depends on how the constraint sequence of P interacts with the pre-existing coherent structures in Ψ_S. If the structures match well, the constraints can efficiently activate existing patterns, making the generative process smooth (low G value); if the match is poor, a large amount of generative action Ξ is required to build structures from scratch (high G value).

To clearly illustrate this principle of relativity and avoid the insurmountable complexity of modeling real adult expert potential fields (their historical imprints are too deep, their associative networks too vast), this paper adopts a highly simplified yet transparently principled thought experiment—"baby counting candies"—to construct a quantifiable general model.

2. Thought Experiment: Intelligent Relativity in Baby Counting Candies

2.1 Task and Constraint Decomposition

Consider a specific task P: "From a pile of mixed objects, select all strawberry-flavored candies whose number is exactly three." Decompose it logically into an ordered constraint sequence: - c_1: The object must be a **candy** (excludes non-candy objects). - c_2: The candy's flavor must be **strawberry** (excludes other flavors). - c_3: The number of candies must be **three** (excludes other quantities).

The **objective exclusion ratios** p_i for a blank agent are set as: $p_1 = 1$ (focusing from all objects to candies), $p_2 = 0.75$ (assuming strawberry flavor constitutes 25%), $p_3 = 0.8$ (selecting 3 from 1-10 candies).

2.2 Potential Fields of Different Agents and Coherence Matching Degree

Define the **matching degree** $m_i \in [0, 1]$ as the strength of the portion of the agent's potential field structure that is **coherent** with constraint c_i. According to the "incoherence principle" of Dynamic Generative Theory, structures mismatched with the constraint do not participate in generation and thus do not affect the matching degree.

We design three simplified agents: - **Agent A (Basic Baby)**: Possesses the most basic relevant concepts. Has a vague recognition of candies ($m_1 = 0.3$), can identify strawberry flavor ($m_2 = 0.4$), knows the number three ($m_3 = 0.2$). No other strong associative knowledge. - **Agent B (Larger Baby, with Irrelevant Knowledge)**: Has richer candy-related experience (e.g., knows price, brand), but this knowledge is **incoherent** with the current task constraints. The coherent part might be stronger: more accurate candy recognition ($m_1 = 0.5$). Flavor and number recognition abilities are the same as A ($m_2 = 0.4, m_3 = 0.2$). **Price knowledge remains silent throughout, neither interfering nor helping.** - **Agent C (Expert Baby, with Strong Associative**

Structure): In daily experience, **strawberry flavor** and **number three** have formed a strong internal association through repeated co-occurrence (e.g., always receiving 3 strawberry candies). Therefore, its coherent structure is highly specialized: candy recognition ($m_1 = 0.5$); when facing the strawberry flavor constraint, the activated structure already includes an expectation for number three ($m_2 = 0.8$); when facing the number three constraint, the activated structure already includes an expectation for strawberry flavor ($m_3 = 0.9$).

2.3 Calculation and Comparison of Generative Complexity

The generative complexity for agent S is defined as: $G_S = \sum_{i=1}^{3} p_i \cdot (1 - m_i^S)$. Calculations yield: - $G_A = 1.79$ - $G_B = 1.59$ - $G_C = 0.73$

Analysis of Results: 1. **B's irrelevant knowledge does not interfere**: B's extra knowledge (price) does not participate in generation due to incoherence with the constraints. Its G value is slightly lower than A's, solely due to its stronger coherent structure for "candy recognition" (higher m_1). 2. **C's associative structure yields a huge advantage**: Due to the strong association between strawberry flavor and number three, C has extremely high matching degrees for constraints c_2 and c_3, making the generative process highly efficient, with a G value far lower than A and B. 3. **Three difficulties for the same problem**: There is no "absolute difficulty" for task P. For A it is a relatively hard task ($G = 1.79$), for B a medium task ($G = 1.59$), and for C an easy task ($G = 0.73$). Difficulty is relative.

3. Formal Framework: Core Definitions of the General Theory of Intelligent Relativity

Definition 1 (Coherence Matching Degree Function) Let the potential field of agent S be Ψ_S. The strength of the coherent structure activated by constraint c at the moment of generation is measured by the matching degree function:

$$\mu(c, \Psi_S) \in [0, 1]$$

where $\mu = 1$ indicates the constraint perfectly matches existing structures in the potential field, requiring no new construction; $\mu = 0$ indicates no coherent structure exists, requiring generation from scratch.

Definition 2 (Generalized Generative Complexity) For a problem P with its constraint sequence $\langle c_1, c_2, ..., c_m \rangle$ and corresponding objective exclusion ratios $\langle p_1, p_2, ..., p_m \rangle$, the generalized generative complexity of P for S is:

$$G(P, S) = \sum_{i=1}^{m} p_i \cdot [1 - \mu(c_i, \Psi_S)]$$

It measures the expected minimal amount of generative action (in units of Ξ) that **a specific agent S** must expend to solve P.

Proposition (Intelligent Relativity) The intelligence $\mathcal{I}(P, S)$ exhibited by agent S on problem P can be operationally defined as a decreasing function of the generalized generative complexity, for example:

$$\mathcal{I}(P, S) = \frac{1}{G(P, S)}$$

Thus, intelligence is **relational and domain-specific**, uniquely determined by the matching degree between Ψ_S and the constraint sequence of P.

4. Why Start with a Baby Model: On the Infeasibility of Modeling Adult Experts and the Absence of a Universal G

Choosing "babies" rather than "adult experts vs. novices" as model agents is not an evasion of complexity but stems from dual considerations of theoretical rigor and empirical feasibility:

1. **Modeling Disaster of Historical Depth**: The potential field of an adult expert is woven from decades of highly personalized practice and experience; its coherent structure (Ψ_S) is an extremely high-dimensional, nonlinear historical function. Attempting a "1:1 modeling" to precisely compute $\mu(c_i, \Psi_S)$ is theoretically infeasible and practically meaningless. 2. **Incommensurability of Associations**: Even if two experts can solve the same difficult problem, their internally invoked associative pathways may be entirely different (e.g., a geometer's vs. an algebraist's thought process proving the same theorem). Their high matching degree (low G value) stems from different Ψ_S structures. This reveals the **multiple realizability** of intelligent solutions. 3. **Root of G's Non-Universality**: From the formula $G(P, S)$, its value directly depends on $\mu(c_i, \Psi_S)$, and this matching degree is a product of **individual history (objective practice) and the accumulation of subjective experience**. Since everyone's history is unique, their potential field structure is also unique; therefore, **there exists no universal G(P) that can define the "objective difficulty" of a problem**. The $G(P)$ in the Special Theory is merely a special case of the General Theory when Ψ_S is the empty set, an idealized theoretical reference. 4. **Illuminating Power of the Baby Model**: The baby's potential field is relatively "clean", with fewer historical variables, allowing us to strip away irrelevant factors and clearly demonstrate the core mechanism of **"how different initial structures lead to different generative complexity"**. It proves that differences in intelligence can be fully explained at the simplest cognitive level by differences in structural matching degree, without invoking a mysterious "general intelligence" factor.

5. Conclusion and Outlook: Towards a Truly Relational Cognitive Science

The General Theory of Intelligent Relativity provides a dynamical, quantitative framework for intelligence: - **It unifies the explanation of expert advantage**: Not stemming from a "faster processor", but from their potential field possessing coherent structures highly matched to domain problems. - **It explains learning and expertise accumulation**: The essence is to increase historical depth H in a specific domain, thereby enhancing coherence degree C and lowering the G value for that class of problems. - **It dispels the myth of "innate intelligence"**: So-called "talent" may simply be the initial high matching degree between an individual's early-formed potential field structure and an important domain. - **It raises fundamental questions about traditional IQ tests**: IQ scores merely measure the matching degree between an individual's potential field and **the standardized structure presumed by the test designers, formed**

within a specific cultural and educational context. It is a narrow, socially constructed indicator of compatibility, not a measure of universal intelligence.

Future empirical research should shift towards: 1. Designing ingenious behavioral experiments, using simplified tasks (e.g., variants of the improved "counting candies" task), to manipulate subjects' prior associative training and directly test the predictive power of matching degree μ on proxies for generative complexity (such as reaction time, eye movement patterns, EEG features). 2. Developing non-invasive neural representation methods to attempt to characterize the strength of coherent brain networks activated by specific constraints, as a physiological proxy for μ. 3. Reflecting on educational practice based on this framework: The core goal of education should perhaps not be to impart isolated knowledge, but to **help students construct rich potential field structures with high internal coherence and external compatibility with problems**.

Ultimately, the General Theory of Intelligent Relativity invites us to view wisdom with fresh eyes: It resides not within the skull, but in the **dynamic, generative, resonant relationship between the historically sculpted structure of the individual and the problem forms presented by the world**.

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