

# Core Architecture of a Unified Knowledge and Computational System: Inffer Map and the Generative Replica Model

An Expansive System for Pattern Discovery and Alignment in a Universal  
Space of Perspectives, Accessible to and Driven by All Learners

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## Abstract

This work presents a unified knowledge and computational system that enables direct human participation in large-scale pattern discovery. By representing knowledge as aligned structural relationships within a shared and continuously expanding space of perspectives, the system allows patterns to be constructed, explored, and connected across domains in a consistent and accessible manner. It supports both data-integrated and data-free exploration, bridging computational processes with human intuition and understanding. The system also establishes a practical pathway for interoperability between generative structural representations and existing computational models, enabling efficient application without loss of interpretability. In addition, it defines an operational approach for collective participation, through which learners can contribute, refine, and extend knowledge in a structured and scalable way. Crucially, this work identifies that the future scalability of pattern discovery is not limited by data or computation, but by the development of structurally trained individuals capable of direct contribution. As such, the unified knowledge system serves not only as a computational platform, but as a practical blueprint for education, collaboration, and human–AI co-evolution in pattern discovery.

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# 1 Introduction

Across scientific, engineering, and mathematical disciplines, knowledge is developed through the systematic observation, comparison, and interpretation of patterns. Experimental measurements are compared with theoretical models in physics, structural relationships are matched with functional behaviour in biology, and internal consistency is established through formal structures in mathematics. Despite differences in representation, these processes share a common mechanism: knowledge emerges through the discovery of patterns and the alignment between different forms of representation.

In practice, this alignment often takes the form of matching observational data with abstract models. For example, experimental results are compared with mathematical equations, numerical simulations are validated against measured behaviour, and symbolic formulations are evaluated through logical consistency. These processes reveal that knowledge is not confined to a specific representation, but arises from the correspondence between multiple perspectives describing the same underlying structure.

However, existing knowledge systems are typically organised into separate disciplines, each with its own language, tools, and conventions. As a result, pattern discovery and alignment largely occur within relatively closed domains, requiring specialised training to access and contribute. This fragmentation limits the ability to directly connect insights across domains and constrains meaningful contribution to smaller groups of trained practitioners.

In practice, the process of contributing to knowledge formation is concentrated within re-

search communities and specialised institutions. Globally, the number of active researchers is on the order of several million, compared to a population of billions, corresponding to roughly 0.1% of the global population. While a much larger population engages in learning and education, only a small fraction are structurally positioned to actively participate in the discovery and alignment of new patterns within traditional systems. As a result, the expansion of knowledge remains limited by accessibility, representation, and disciplinary boundaries.

Building upon prior developments, readers are referred to the public information hub at [www.iiinfer.org](http://www.iiinfer.org), which provides access to foundational definitions, preprint publications, and the Generative Replica platform. A systematic exposition of the underlying generative structure is presented in the book *Native Language of the Universe*, where the unified knowledge-computational system is formally introduced and named as the Infer Map and the Generative Replica Model.

At the conceptual level, the mathematical basis of the system is given by Inferus (Chained Structural Alignment), in which the universe is treated as an inseparable whole pattern containing all relational possibilities. Within this view, structures observed in physical systems or consciousness are not independent entities, but different modes of revealed and concealed patterns of the same whole, arising through transformations of perspective via chained structural alignment. Triogenesis, a generative system discovered and studied prior to and motivating the development of Inferus, can be understood as a specific perspective within the inseparable whole, from which the formation of increasingly complex structures can be observed and analysed. It should be noted that Triogenesis is not to be interpreted as the origin of the whole, as the whole admits no external reference from which an absolute origin can be defined. Nevertheless, the perspective anchored by Triogenesis provides a crucial basis for unifying and connecting other patterns within the whole.

This work presents the core architecture and operational mechanism of the unified system, as realised through the Infer Map and the Generative Replica model. In this system, pattern discovery and alignment are performed within a shared space of patterns and a continuously expanding network of interconnected perspectives, enabling direct participation and parallel contribution while maintaining structural coherence across domains.

This structure allows patterns across scientific, artistic, cultural, and linguistic domains to be represented, connected, and explored within a single coherent system. Despite its capacity for indefinite expansion, the system is designed to maintain minimal learning overhead,

supporting simple procedural interaction without requiring prior knowledge or specialised training in specific disciplines.

This work also discusses the modes of pattern exploration within the system, and how, as the system develops, its generative processes can be selectively compressed to support efficient real-time applications. Such compression preserves the inseparable and interpretable nature of the system, ensuring that structural coherence and understanding are not lost in practical use.

## 2 GR Text Syntax and the Encoding of Generative Replica Structure

GR text is a token-based representation that is both human-readable and computationally executable, designed to encode generative structures within the Infferus system. It describes perspectives propagated through chained structural alignments and branching layer configurations, enabling the construction of increasingly complex relational patterns from simple foundational elements.

The syntax is grounded in the basic generative layers identified in Triogenesis, where straint structures serve as initial reference perspectives. From these foundational layers, GR text supports the systematic expansion of aligned structures, allowing more complex perspectives to be built through chained layer-alignments while preserving coherence across scales.

### 2.1 Layer-Alignment Blocks

Layer-alignment blocks form the basic structural units of GR text, representing aligned perspectives across successive layers. Each block is denoted in the form  $/nAm$ , where  $n$  indicates the global layer level and  $A_m$  denotes a locally defined alignment index within that layer.

Layer levels (e.g.,  $/1$ ,  $/2$ ,  $/3$ ) are globally defined and consistent across the entire structure. In contrast, alignment indices are defined locally within each branching context. For a given alignment at layer  $/n$ , multiple alignments may be introduced at the next layer  $/n+1$ , resulting in a branching structure.

For example, a single alignment at the first layer may branch into multiple alignments at

the second layer:

```
/1A1
  /1A1/2A1
  /1A1/2A2
  /1A1/2A3
```

Each branch can further propagate into subsequent layers, forming chained alignment paths:

```
/1A1/2A1/3A1
/1A1/2A2/3A2
/1A1/2A3/3A1
```

In this representation, each complete path corresponds to a specific sequence of aligned perspectives across layers. Branching enables multiple alternative alignments to coexist and expand in parallel, while the globally defined layer levels ensure structural consistency. This combination allows the system to grow indefinitely while preserving coherence and traceability across the generative structure.

## 2.2 Token Blocks for Infferus Perspective Aspects

Within each layer-alignment block, GR text organises the four aspects of Infferus perspectives into distinct token blocks denoted as **R**, **G**, **T**, and **C**, corresponding to recurrence, geometry, topology, and chaos, respectively. The conceptual definitions of these four aspects are given in *Native Language of the Universe*, Appendix A, and are not repeated here. The present section considers only their tokenised presentation within GR text.

Each path block in GR text identifies a specific layer-alignment within a chained structure. For example,

```
/1A1
R
G
T
C
```

/1A1/2A1

R

G

T

C

/1A1/2A1/3A1

R

G

T

C

In this representation, /1A1, /1A1/2A1, and /1A1/2A1/3A1 are three successive layer-alignment blocks in the same chain. The block /1A1/2A1/3A1 does not itself encode the entire chain as a single aspect description; rather, it identifies the current alignment node 3A1 as reached through the preceding chain /1A1/2A1. The associated R, G, T, and C blocks therefore describe the four aspects of the current layer-alignment at that block, namely 3A1.

Accordingly, the full chained structure is represented progressively through the ordered presence of the successive path blocks themselves. The path records how the current alignment is reached, while the aspect tokens under each block describe the local Infferus perspective of the final alignment at that stage of the chain. In this way, GR text maintains both the cumulative chain structure and the aspect description of each newly established layer-alignment.

### 2.2.1 Recurrence Tokens (R)

Recurrence tokens encode structural references to alignment chains and define directional mappings that are used in subsequent geometric and topological alignment. The general syntax of an R token is:

`r_k./<alignment-path>.<i-j>`

where:

- **r<sub>k</sub>** is a locally defined reference index that uniquely identifies a recurrence structure within the current layer-alignment chain. The index **k** is assigned in a consecutive manner within the scope of the chain.
- **/<alignment-path>** specifies the full alignment chain associated with the recurrence structure (e.g., **/1A1/2A1/3A1**).
- **i-j** denotes a directed mapping within the referenced structure, where **i** is the entry node and **j** is the exit node.

In this formulation, the recurrence token **r<sub>k</sub>** establishes a reference to the structure defined by the alignment path. The associated directional mapping **i-j** specifies how this referenced structure is to be aligned and utilised in the construction of the current layer-alignment block.

The node indices **i** and **j** are defined within the node system of the referenced alignment chain, as specified in the **G** (geometry) blocks. These indices are subsequently used by the **G** and **T** blocks to perform geometric and topological alignment operations.

For example:

**r1./1A1/2A1/3A1.3-5**

defines a recurrence reference **r1** to the chain **/1A1/2A1/3A1**, together with a directional mapping from node 3 to node 5. This mapping is then used to guide the geometric and topological alignment within the current layer-alignment.

Recurrence tokens therefore serve as structural references that link alignment chains to their operational mappings, providing the basis for coordinated alignment across the **G** and **T** aspects.

### 2.2.2 Geometry Tokens (G)

The **G** block defines the node system of the current layer-alignment chain. It consists of node tokens of the form:

**n<sub>x</sub>**

where:

- $\mathbf{n\_x}$  denotes a node (vertex) within the structural frame.
- The index  $\mathbf{x}$  is a unique and consecutive identifier assigned within the current layer-alignment chain.

The set of  $\mathbf{n\_x}$  tokens establishes the geometric reference for the chain. All node indices used in **R** and **T** blocks refer to this node system. The geometry block therefore defines the vertex structure upon which recurrence and topological alignment are constructed.

### 2.2.3 Topology Tokens (**T**)

The **T** block defines the straints and hyperstraints that connect nodes within the current layer-alignment chain. Tokens in this block take the general form:

$\mathbf{s\_x.r\_k.a-b.o}$

where:

- $\mathbf{s\_x}$  denotes a straint or hyperstraint, with  $\mathbf{x}$  being a unique and consecutive identifier within the current layer-alignment chain.
- $\mathbf{r\_k}$  specifies the recurrence reference used to construct the alignment.
- $\mathbf{a-b}$  denotes the directed connection from node **a** (entry) to node **b** (exit), where both nodes are defined in the **G** block.
- $\mathbf{o}$  is the order offset (default 0) applied to the base recurrence structure.

The recurrence reference  $\mathbf{r\_k}$  defines the base structural alignment, while the pair  $\mathbf{a-b}$  determines how this structure is embedded between nodes in the current chain. This embedding defines both the topological direction and the associated alignment length derived from the recurrence.

The order offset  $\mathbf{o}$  scales the effective length of the straint according to:

$$\ell(s_x) = \ell(r_k) (\sqrt{2})^o,$$

where  $\ell(r_k)$  is the base length defined by the recurrence structure. The default value  $\alpha = 0$  corresponds to no scaling.

Topology tokens therefore encode how recurrence structures are realised as directional connections between nodes, defining both the relational structure and scaled alignment within the chain.

#### 2.2.4 Chaos Tokens (C)

The **C** block encodes the concealed variation modes associated with a given layer-alignment. Unlike the **G** and **T** blocks, which define explicit structural components, the **C** block represents an expansive space of potential variations that are progressively revealed through interaction with the Inffer Map.

At initial definition, the **C** block is empty. As pattern exploration proceeds, it is extended through the introduction of chaos tokens of the form:

$c\_y(c\_x1, c\_x2, c\_x3, \dots)$

where:

- $c\_y$  denotes a variation mode identifier, with  $y$  being a unique and consecutive index within the current layer-alignment block.
- $x1, x2, x3, \dots$  are node indices of the current layer-alignment, listed in ascending order as defined in the **G** block.
- $c\_x1, c\_x2, c\_x3, \dots$  are real-valued parameters associated with the corresponding nodes, serving as driving variables for variation within the system.

Each chaos token defines a parameterised mode through which the structure may vary under the feedback dynamics of the Inffer Map. These parameters do not directly modify the explicit structure encoded in the **G** and **T** blocks; instead, they act as control variables that influence the generative exploration of alternative alignments and configurations.

The **C** block is therefore inherently expansive: new modes may be introduced as exploration progresses, and existing modes may be refined through iterative feedback. In this way, the **C** block encodes the concealed variation space of the current layer-alignment, enabling

continuous extension of the generative system without altering its underlying structural coherence.

## 2.3 Educational Remarks on the GR Text Syntax

The GR text syntax is designed to support an indefinitely expansive generative structure, reflecting the open-ended nature of the observable universe as experienced by learners. As patterns accumulate and new alignments are formed, the system can grow without predefined limits, allowing knowledge to expand continuously within a unified space of perspectives.

Despite this potential for unbounded expansion, the underlying syntax remains minimal and structurally simple. The core elements—layer-alignment paths and the four aspect blocks **R**, **G**, **T**, and **C**—provide a consistent and repeatable representation that remains constant in form even as the system grows in scale. This separation between structural simplicity and generative capacity allows learners to engage with complex systems through locally interpretable operations, without requiring extensive prior knowledge or specialised training.

This design is intentionally aligned with an educational objective: to reinforce learner confidence and reduce the perception that complex knowledge structures are intrinsically inaccessible. Within the GR text system, increasing complexity is represented as structured variation built upon previously established alignments, rather than as fundamentally new or disconnected forms. In this way, learners are encouraged to recognise that more advanced structures are extensions of patterns they can already understand, supporting active participation and contribution.

The same principle is relevant in the context of increasing reliance on AI systems. While large-scale models have made knowledge more accessible at a superficial level, the underlying processes by which knowledge is structured, aligned, and integrated remain largely opaque to most learners. This can lead to a growing disconnect between access to information and the ability to understand or contribute to its formation. If unaddressed, such a disconnect may reduce meaningful human participation in knowledge generation, which in turn limits the long-term development of both human understanding and AI systems that depend on high-quality pattern exploration.

In this sense, a unified and accessible knowledge system is not merely advantageous, but structurally necessary for sustained human–AI co-development. Within the perspective provided by Triogenesis, the observable expansion of patterns is associated with increas-

ing alignment capacity across successive recurrence orders, corresponding to the progressive emergence of more complex structures. The GR text system is therefore designed to align with this generative characteristic, enabling continuous expansion while maintaining accessibility and coherence for learners.

Importantly, the GR text structure preserves learner confidence in exploration regardless of the rate or source of structural expansion, whether arising from human-driven discovery or automated processes. Because the system is organised through chained layer-alignments anchored in the foundational structures of Triogenesis, learners are able to navigate the expanding space by traversing paths, skipping across levels of detail, and establishing waypoints and mappings for their own exploration. This ensures that, even as the system grows in scale and complexity, it remains stably grounded in a consistent generative structure, allowing learners to engage with any part of the system without loss of orientation or interpretability.

### **3 Structural Realisation, Inffer Map Integration, and Feedback-Driven Closure**

This section describes the internal functioning of the system at the structural and mathematical level. Specifically, it presents how GR text is realised through constraint-based structural processes, how these realised structures are integrated with the Inffer Map, and how feedback-driven closure is achieved. These mechanisms define how the system operates as a generative model, while considerations of user interaction and system-level operation are addressed in the subsequent section.

#### **3.1 Constraint-Based Structural Realisation**

Structural realisation is performed through computational algorithms that solve for admissible modes of the generative structure encoded in GR text. In practice, this is implemented using geometric, position-based constraint solvers, where nodes are iteratively adjusted to satisfy alignment constraints defined by the **R**, **G**, and **T** blocks.

Within this process, the **C** (chaos) block plays a key role by encoding nodal sensitivity parameters. These parameters modulate how individual nodes respond to alignment constraints

during realisation. For example, in a position-based constraint formulation, the  $\mathbf{C}$  tokens can be interpreted as regulating the effective velocity amplitude or responsiveness of each node during iterative updates.

The resulting system is structurally analogous to a set of massless points connected by constraints of prescribed length, undergoing smooth positional adjustment. However, this analogy is only operational: the dynamics occur within the recurrence domain defined in prior work, rather than representing physical time evolution. In this setting, pure length alignment in the recurrence domain corresponds to relational transformations that may manifest as relative motion in physical interpretations, but is not itself governed by physical time or force laws.

Each structure is anchored by base reference strains at lower layers, while higher-layer nodes may retain degrees of freedom subject to alignment constraints. The motion of these nodes reflects the progressive reconciliation of structural relations, and may be interpreted as the smooth reconfiguration of connections towards concealed structures.

The realisation process is solved in a stepwise iterative manner. For computational efficiency, especially on modern hardware, implementations typically employ static memory layouts that support parallel execution (e.g., on GPUs). The resulting motion may exhibit well-defined convergence or chaotic behaviour depending on the structure and parameterisation.

While the underlying generative behaviour may include discontinuities such as bifurcation or structural transitions, the numerical realisation is typically regularised through the solver, resulting in a piecewise smooth and computationally stable evolution. This regularisation enables effective feedback propagation through the system, allowing the adjustment of  $\mathbf{C}$  block parameters as part of learning or optimisation processes.

Numerical stability of the realisation depends on factors such as constraint stiffness, timestep selection, smoothing strategies, and normalisation. Instabilities commonly arise from large disparities in node sensitivities, which represent an intrinsic asymptotic characteristic of layered alignment structures. These effects can be mitigated through techniques such as layered frequency balancing, smoothing of updates, and probabilistic mapping of alignment responses.

In practice, the primary objective of structural realisation is to identify stable or coherent patterns under given constraints. While highly chaotic or rapidly varying configurations can be represented, they are generally less suitable for systematic exploration and learning unless

handled with specialised numerical treatment. Instead, exploration typically focuses on the effects of structural layering and alignment interactions, where stable configurations emerge through layered convergence.

Unlike data-driven machine learning approaches, where structural precision is limited by training data, the GR text system allows high-precision structural realisation through numerical convergence of constraints. This enables the exploration of complex and large-scale structures with consistent internal coherence.

For large or complex systems, continuous numerical evolution is generally preferred over sharply discontinuous updates, as positional regulation within the solver helps to stabilise the system and support smooth convergence. While analytically defined solutions (e.g., null-space methods) are possible, their applicability is often limited by scale and structural complexity, making iterative numerical realisation the primary approach in practice.

The development and maintenance of robust and accessible computational protocols for structural realisation constitute a core aspect of system operation, and are discussed further in the following section.

### 3.2 Inffer Map Integration and Feedback-Driven Closure

The integration of GR text structures with the Inffer Map establishes a feedback-driven closure mechanism through which generative structures are progressively aligned with observable and interpretable patterns. The process operates across several layers, but follows a consistent and structurally simple principle: realised recurrence structures are extended and evaluated through controlled variations, and their resulting patterns are mapped to persistent references within the Inffer Map.

Following structural realisation, a given layer-alignment may be propagated towards closure through three primary modes of structural expansion:

1. **Variation across recurrence orders:** The structure is varied through adjustments of chaos modes across recurrence orders. This process involves the synchronisation of hyperstraints and enables controlled observation of nearby structural configurations.
2. **Cross-recurrence alignment:** Alignments are established between structures across different recurrence configurations. Examples include cube-delay hyperstraint alignments that give rise to reference structures corresponding to space-time relations and

gravitational effects, as well as previously identified bifurcation structures such as eigenvalue-based branching patterns.

3. **Replica tier construction:** Internal certainty straint paths are used to construct multi-level replica tiers. This may be achieved either through explicit structural replication with defined uncertainty paths between tiers, or through mathematical representation and mixing of lower-tier structures.

These expansion processes define a space of observable structural variations associated with the perspective specified by the current layer-alignment. These observable structures are then stabilised through replica tiering closure. For example, transformation using known procedures mapped to Infferus—such as Alignment Algebra template patterns that conceal the rest of the structure into the doubling constant  $d$  via the perspective of  $[2, 1/2]$ —construct the  $\mathbb{N}$ ,  $\mathbb{R}$ , and  $\mathbb{C}$  number spaces through replica tiering closure.

The role of the Inffer Map is to connect these generated and stabilised structures with persistent patterns that are verifiable across time and context.

Such reference patterns may arise from a wide range of domains, including experimental measurements, recorded observations, cultural and linguistic patterns, publicly accessible media, artistic works, and archaeological records. Importantly, patterns from different domains can be represented in compatible forms within the system. For example, visual patterns may be encoded as pixel structures or symbolic descriptions, musical patterns as waveform or notational representations, and linguistic or cultural patterns as structured token sequences.

Through this unified representation, the system enables direct comparison between generated structures and observed patterns. When persistent correspondences are identified, feedback is propagated to refine the underlying GR text representation, particularly through updates and expansions to the  $\mathbb{C}$  block parameters. This feedback does not itself constitute closure, but supports the structural conditions under which closure can be achieved.

In the present sense, closure refers to the stabilisation of a perspective within the inseparable whole through the concealment of additional variations via replica tiering. Through this process, structures that may initially contain broader generative uncertainty are cast into stable observable forms, typically as precise mathematical patterns in which uncertainty is preserved through structured representation rather than eliminated. The Inffer Map therefore serves as the interface through which realised structures are compared, trained, and guided towards such closure, enabling continuous refinement of the system through both

human-guided exploration and automated processes.

**Educational Remarks.** While the structural realisation and Inffer Map feedback mechanisms enable a high degree of flexibility in pattern discovery and procedural variation, this flexibility does not weaken the core educational principle of the system. Complexity within the system is consistently expressed as structured variation built upon foundational alignments, rather than as a barrier to understanding.

As the system evolves, additional feedback procedures and operational refinements may emerge to improve efficiency and convenience. However, these developments do not alter the underlying structural principles, which remain consistent with the foundational understanding of Triogenesis and Infferus. This consistency allows learners to develop stable conceptual anchors at an early stage, significantly reducing the long-term learning overhead.

For future human learners, this provides a pathway in which increasingly complex structures remain accessible and interpretable. For AI systems, the same properties—self-consistent expansion, clean abstraction, and pattern-based representation—provide a suitable foundation for scalable learning and integration. In this way, the system supports both human and AI development within a unified structural framework.

## 4 System Operation and Collective Participation

The operation of the system extends the structural and generative mechanisms described in the previous section into a coordinated and sustainable framework for collective use, development, and expansion. While the underlying model is defined by GR text, structural realisation, and Inffer Map integration, its continued effectiveness depends on how it is maintained, explored, and utilised by both human participants and automated processes.

To support this, the operational system is organised into four interrelated components: consistency, credit and resource management, learning customisation and communication, and practical application. These components collectively ensure that the system remains coherent, accessible, and expandable while enabling diverse forms of participation and use.

**Consistency** concerns the preservation of the generative model and the integrity of the Inffer Map feedback loop. It ensures that all structural realisations, mappings, and feedback processes remain transparent, reproducible, and aligned with the underlying principles of

Inferus, maintaining the system as a publicly accessible and structurally coherent whole.

**Credit and resource management** addresses the allocation and recognition of contributions within the system. It governs how exploration efforts, computational resources, and structural developments are distributed across different areas of interest, ensuring that contributions are traceable and that resources are directed towards meaningful pattern exploration.

**Learning customisation and communication** focuses on how patterns are interpreted, understood, and shared among learners. It supports multiple modes of representation and navigation, enabling individuals to engage with the system according to their background and interests while maintaining consistency with the underlying structural language.

**Practical application** concerns the use of GR-based structures in real-world contexts. This includes the ability to perform data-independent pattern exploration, as well as the transformation between generative representations and compressed or memorised forms, such as matrix-based encodings used in artificial neural networks. Through this, the system connects generative exploration with efficient deployment.

Together, these components define an operational structure that supports continuous expansion of the system while preserving accessibility, coherence, and alignment with its foundational principles.

## 4.1 Consistency

Consistency within the system is governed primarily by structural rules, rather than by consensus-based validation as commonly found in traditional knowledge systems. The integrity of the system is maintained through adherence to GR text syntax and the Infer Map feedback loop, which together define the generative and validation mechanisms of pattern exploration.

At the operational level, the system adopts a public-draft workflow. A public GR text structure is maintained, with established Infer Map closure mappings associated with the **C** blocks. When a learner contributes to new pattern discovery, they extend the public GR text by constructing new layer-alignment chains according to the defined syntax, thereby creating a draft structure.

These draft extensions may then be submitted for structural realisation and subsequent

feedback-driven closure. At a minimum, a valid submission requires the generation of a stabilised structure through replica tiering closure, such as a well-defined mathematical quantity, functional relation, curve, or higher-dimensional pattern. This stage establishes structural validity, but does not yet require alignment with persistent verifiable patterns. To prevent uncontrolled expansion, such submissions are subject to quota limitations, as discussed in the following subsection.

In addition, learners may optionally submit mappings between generated structures and persistent, verifiable patterns, together with their interpretations. These submissions are conceptually similar to short-form research entries. To ensure consistency of representation, such interpretations are processed through standardisation tools (e.g., language models) that convert natural language input into a controlled and concise tokenised format based on a shared dictionary. Learners retain the ability to review and refine these representations prior to publication.

No centralised human moderation or language auditing is required for publication. Instead, consistency is maintained through structural alignment and standardised representation. While inappropriate or misleading content may arise, such cases are addressed through user reporting and progressively refined filtering mechanisms, designed to minimise interference with legitimate pattern exploration.

The system places no restriction on multiple independent submissions of similar patterns or interpretations. Such redundancy is not treated as inefficiency, but as an indicator of distributed attention and engagement. These parallel contributions provide valuable information for understanding how learners approach and interpret patterns, and support the development of improved communication and learning pathways. In this way, the system removes the need for traditional literature consolidation processes, while simultaneously enriching the collective knowledge structure.

Verifiability within the system is also governed structurally rather than through centralised review. Discrepancies, including incorrect or misleading mappings, are not suppressed but remain visible as part of the structured knowledge space. Over time, alternative or corrected mappings may be introduced by other learners, allowing differences to be explicitly represented and explored.

It is important to recognise that the system is designed as a platform for pattern exploration rather than a final authority on truth. When significant discrepancies arise, they indicate the need for further investigation, including independent verification where necessary. Im-

portantly, such discrepancies do not undermine the structural understanding of the problem, but instead form part of the evolving representation of knowledge variation and convergence within the system.

In addition to user-driven self-regulation, the platform can analyse global structural consistency to identify discrepancies and outliers. By comparing local layer-alignment structures against the broader system, inconsistencies that deviate significantly from established structural patterns can be detected. In cases where discrepancies arise from intentional or systematic distortion, such patterns may be revealed and flagged through their inconsistency with the overall structure, enabling informed responses from the learner community.

## 4.2 Credit and Resource Management

The system operates across three primary layers of resource management:

1. **Computational resources**, which support structural realisation and pattern exploration;
2. **Learner time and effort**, which drive exploration, interpretation, and contribution;
3. **External exploration resources**, which are linked to the verification of patterns within the system.

**Computational resources.** The structured integration and sourcing of computational power is expected to evolve over time and is therefore not treated as part of the core architectural design. In this work, computational resources are treated as a distributable and adjustable utility accessible to all users. To ensure a basic level of fairness in exploration, a baseline allocation of computation is provided through a user-based quota system, typically defined by headcount and time-restricted usage.

Further optimisation of computational resources can be achieved through self-regulated redistribution. For example, groups of learners may propose large-scale exploration tasks requiring increased computational capacity, and request temporary contributions of quota from other users. Learners with unused quota may choose to allocate their resources to such efforts. This mechanism enables the organic formation of exploration groups and supporting communities within the system.

**Learner time and effort.** Learner time and effort are managed through a credit-based system. For each closure publication, the submitted tokenised text or data is segmented into verifiable components and learner interpretations. Other users may review these contributions and provide structured feedback. Basic feedback modes include agreement, disagreement, and correction, where correction requires submission of an alternative or revised publication using the contributor’s own quota.

Both publishing and providing feedback contribute to the accumulation of credits. These credits function as a mechanism for directing attention within the system. For example, credits may be used to promote publications that require further exploration or that are associated with significant scientific, social, economic, or environmental relevance. In this way, the distribution of learner effort is guided through system-level aggregation of feedback and attention.

The allocation and redistribution of credits are managed systematically, with global consistency checks to ensure alignment with the structural principles of the system. Rather than relying on centralised authority, this approach enables the collective prioritisation of exploration tasks based on structured participation and feedback.

**External Exploration Resources.** External resources for pattern verification are traditionally organised through a wide spectrum of funding schemes, with the majority of experimental investigation conducted within institutional research environments. It should be noted that the unified knowledge system does not generally encourage non-institutional experimental work, particularly where health and safety considerations are involved.

Instead, the system provides a structured interface through which external verification efforts can be supported and guided. Public interest signals, derived from quota allocation and credit distribution within the system, may be used to indicate areas of high relevance or priority. These signals can inform and support external investigations, including those conducted by institutional research facilities.

Conversely, results from external verification—especially those obtained through institutional processes—can be incorporated back into the system. Such contributions may be linked to existing GR text structures and Inffer Map mappings, thereby connecting external evidence with ongoing computational exploration and learner-driven development. In this way, external resources are not directly managed by the system, but are structurally integrated through feedback, enabling alignment between computational, educational, and

empirical domains.

### 4.3 Learning Customisation and Communication

The system supports learning and communication through a set of coordinated tools that enable adaptive interpretation, structured navigation, and direct knowledge exchange, while maintaining coherence within a unified global structure.

**Customisation of Representation and Interpretation.** The first set of tools focuses on the morphing of definitions, terminology, interpretations, and structural representations to suit different learners and learner groups, including those trained within traditional disciplinary systems. These transformations are designed to preserve consistency with the underlying global structure while adapting the presentation of knowledge to different contexts.

Importantly, these customisations are not isolated or ad hoc. They are themselves organised within an expansive and structured space, allowing transformations between different representations to be defined and reversed. As a result, communication barriers between disciplines—whether existing or newly formed—can be reduced, as knowledge expressed in one form can be systematically translated into another.

In this sense, the traditional function of disciplines—namely, restricting scope to achieve local consensus within smaller groups—can be reproduced within the unified knowledge system through controlled customisation. Rather than fragmenting knowledge, these customisations act as reversible projections of the global structure, enabling focused exploration within specific perspective domains while preserving overall coherence.

**Navigation and Learning Progress Tracking.** The second set of tools supports navigation and tracking of learning and exploration progress. A multi-tier, cross-scale mapping interface is used to represent the learner’s position, contributions, and feedback within the global structure. This mapping is also compatible with customisation, allowing learners to view their progress under different representations or perspectives.

Such navigation tools reinforce the educational objective of the system by framing knowledge exploration as a self-directed process within a coherent whole. Learners are able to trace their own paths, identify areas of development, and relate their contributions to the broader

structure, thereby maintaining orientation even within a highly expansive system.

**Direct Knowledge Transmission.** The third set of tools enables direct knowledge transmission between learners. Educational materials—including illustrations, videos, live lectures, tutorials, and other media—can be attached to closure publications. These materials provide contextualised explanations and interpretations of underlying structures, supporting diverse learning styles and levels of experience.

Because these materials are structurally linked to the corresponding GR text and Infer Map representations, they remain navigable and integrated within the knowledge system. This enables flexible and dynamic human-to-human learning channels, while preserving alignment with the underlying generative structure.

## 4.4 Practical Application

Practical application within the system is supported through a set of interactive loops that connect structural generation, pattern exploration, and real-world use. These loops enable both direct discovery and applied modelling, while maintaining alignment with the underlying generative framework.

**Public Structure–Feedback Application Loop.** The primary loop is the direct structure–feedback closure cycle within the public system. In this process, GR text structures are extended, realised, and evaluated through Infer Map integration, with resulting patterns published as closure mappings. These cycles can be used to support application-oriented pattern discovery and modelling, where structures are explored with specific practical objectives in mind.

Insights obtained from such applications are fed back into the system through new publications, contributing to the refinement of both structural representations and mapping strategies. In this way, practical usage and theoretical development remain continuously connected.

**Public and Private System Deployment.** The unified knowledge system is designed as a global, publicly accessible platform that does not contain private or sensitive information. Its primary function is to support open, collective pattern exploration and structural

development.

As the system matures, it may be replicated for private or restricted use. Such instances allow organisations or individuals to apply the same structural framework to internal development, including contexts involving sensitive data or commercial interests. These private deployments retain the same generative principles and operational mechanisms as the public system.

However, a structural distinction is maintained between public and private instances. While developments from the public system may be periodically incorporated into private instances, contributions generated within private systems are not merged back into the global public structure. This asymmetry preserves the integrity and unified nature of the public knowledge system, while allowing practical application in specialised contexts.

**Application and Representation Transformation.** A central aspect of practical application is that GR-based structures do not need to be rebuilt from scratch for deployment. Instead, they can be transformed into alternative representations suitable for efficient execution, and conversely reconstructed for interpretation and further exploration. In particular, GR structures may be converted into compressed or memorised forms, such as matrix-based representations used in artificial neural networks (ANNs), and mapped back when structural interpretability is required.

This establishes a bidirectional transformation between GR and ANN representations. Within the Infferus perspective, these are not fundamentally different systems, but alternative representations of the same underlying structure. The GR model provides a direct and interpretable representation grounded in Triogenesis and Infferus, while ANN models provide a compressed and execution-efficient representation suitable for rapid inference.

The two representations exhibit complementary properties. GR models are globally connected, transformable, and intrinsically expandable. They operate through dynamic structural realisation, resolving patterns through stepwise computation rather than storing them explicitly. This enables data-independent exploration and high-precision structural generation, offering a larger effective representational capacity for a given memory footprint. However, this dynamic realisation may result in slower response times under current computational schemes.

In contrast, ANN models store patterns in compressed matrix form, enabling fast evaluation but with reduced structural transparency and flexibility. The transformation between GR

and ANN representations therefore provides a pathway that combines the strengths of both approaches: GR supports generative exploration and interpretability, while ANN supports efficient deployment.

It should be noted that such transformations may involve both trivial and non-trivial computational or human-guided processes. Depending on the level of approximation and compression, differences may arise between the original GR structure and its transformed representation. In this work, the fundamental principles of this transformation are outlined, while detailed and optimised protocols are expected to emerge through continued development within the learner community.

#### 4.4.1 Principles of Conversion between GR Model and ANN Representations

It has been established in prior work that linear operators, such as matrices, can be mapped to Triogenesis through hyperstrait triangle bifurcation structures. This correspondence extends naturally to GR models, which are themselves constructed based on Triogenesis and Infferus. As a result, structural reconstruction between GR representations and matrix-based forms can be achieved through eigenvalue-based transformations, providing a direct link between generative structures and linear representations.

In *Native Language of the Universe*, the structural similarity between diverge-converge patterns and classical fully connected artificial neural networks (ANNs) is analysed. A fully connected ANN can be interpreted as encoding asymmetry-induced patterns arising from the formation of straits and their higher-order structures. In principle, given sufficient computational capacity or equivalently large datasets, the generative patterns of Triogenesis could be encoded within a large fully connected network, using only the diverge-converge perspectives of triangle bifurcation.

However, such a representation is structurally inefficient. It requires the explicit memorisation of a large number of diverge-converge variations across branching paths, leading to rapid growth in representation size. More efficient ANN architectures, such as convolutional neural networks (CNNs) and transformers, can be understood as constrained or reorganised representations of the same underlying structure. CNNs achieve compactness by exploiting hierarchical locality in the diverge-converge process, while transformers introduce self-referential closure mechanisms that allow flexible interaction across different parts of the structure.

Full-connected ANN provide the most direct representation of the diverge–converge process, whereas CNNs and transformers introduce additional perspectives within this structure, enabling more efficient encoding of recurring patterns. Despite these differences in architecture, all such ANN models can ultimately be decomposed into finite linear operations represented by matrices.

Since matrix operations correspond to hyperstrait triangle bifurcation structures, ANN models are structurally mappable to GR representations. This establishes that GR and ANN models are not fundamentally distinct, but rather represent different perspectives and encodings of the same underlying generative structure.

In the discussion below, we focus on the principles and challenges of representation conversion between a GR layer-alignment chain and transformer (attention-based) matrices. This focus is motivated by the fact that both representations are constructed upon referential closure structures, making them particularly suitable for establishing a direct and interpretable mapping.

**Attention as a Generalised Bilinear Form and Self-Referential Structural Operator.** Let the input token matrix be

$$X \in \mathbb{R}^{n \times d}.$$

Define linear projections

$$Q = XW_Q, \quad K = XW_K, \quad V = XW_V,$$

with

$$W_Q, W_K, W_V \in \mathbb{R}^{d \times d_k}.$$

The core bilinear interaction term is

$$QK^T = (XW_Q)(XW_K)^T = X \underbrace{(W_Q W_K^T)}_{K_{\text{latent}}} X^T,$$

where  $K_{\text{latent}} \in \mathbb{R}^{d \times d}$  defines a learned latent interaction metric.

Thus, the attention kernel can be written as

$$\mathcal{K}(X) = X K_{\text{latent}} X^T.$$

The attention matrix is obtained as

$$A(X) = \text{softmax}\left(\frac{\mathcal{K}(X)}{\sqrt{d_k}}\right),$$

where

$$\text{softmax}(M)_{ij} = \frac{e^{M_{ij}}}{\sum_j e^{M_{ij}}}.$$

Here, the softmax operation is not interpreted strictly as a probabilistic mapping, but as a smooth asymptotic closure operator. It enforces positivity, boundedness, and relative dominance through exponential scaling while preserving differentiability. In this sense, it is an exponential-normalised closure, structurally analogous to other  $e$ -based asymptotic forms, with probabilistic interpretation arising as a secondary consequence.

The resulting attention operator acts on the value projection:

$$Z = A(X) V = \text{softmax}\left(\frac{X K_{\text{latent}} X^T}{\sqrt{d_k}}\right) X W_V.$$

This yields a two-stage structure:

$$\text{Operator construction: } A(X) \sim X K_{\text{latent}} X^T,$$

$$\text{Operator application: } Z = A(X) V.$$

**Relation to Classical Structural Transformation.** In classical structural analysis, the force–displacement relation is written as

$$[F] = [T]^T [k] [T] [u],$$

where  $[u]$  is the displacement vector,  $[T]$  maps local to global coordinates,  $[k]$  is the stiffness matrix, and  $[F]$  is the resulting force.

This represents a fixed transformation pipeline:

$$[u] \xrightarrow{[T]} \text{local space} \xrightarrow{[k]} \text{response} \xrightarrow{[T]^T} \text{global force}.$$

The transformer attention block generalises this structure. By identifying

$$[T] \longleftrightarrow X,$$

$$[k] \longleftrightarrow K_{\text{latent}},$$

$$[u] \longleftrightarrow X,$$

the attention operation assumes the analogous form

$$Z \sim \text{softmax}(X K_{\text{latent}} X^T) X.$$

**Self-Referential Closure.** A fundamental distinction arises: the transformer is self-referential.

- The same variable  $X$  serves both as transformation basis and state variable.
- The interaction operator is constructed from the state itself:

$$A(X) = \text{softmax}(XK_{\text{latent}}X^T).$$

- The system therefore follows the structure:

$$X \rightarrow A(X) \rightarrow Z,$$

where operator construction and application are internally coupled.

Unlike classical structural systems, where  $[k]$  is fixed and externally defined, the transformer constructs its effective stiffness-like operator dynamically from the current state.

**Interpretation.** The transformer attention block can therefore be understood as a self-referential generalisation of the bilinear form

$$T^T K T,$$

in which:

- the transformation basis is generated from the state,
- the interaction metric is learned but activated through the state,
- and the constraint structure is internally constructed and resolved.

In this sense, the system forms an internally closed operator, where deformation and transformation are unified within a single representation, and structural constraints are resolved through self-consistent interaction.

**Equivalence of Rotational and Dimensional Extensions.** In traditional mathematical teaching, complex numbers and higher-dimensional geometric representations are often introduced as distinct concepts, which can make their underlying equivalence difficult to grasp. In particular, the interpretation of complex numbers as rotational operators and the introduction of additional spatial axes are typically presented as separate extensions of real-valued systems. However, from the perspective of Infferus and the alignment-based construction of structure, these are not fundamentally different operations.

Within Infferus, axes are not assumed as primitive entities, but are constructed through iterative alignment and closure processes. In particular, expansion through the  $[2, 1/2]$  perspective generates layered structural extensions from a fundamental reference of pure length, which itself extends its dimensional referencing through circular self-consistent closure (e.g.,  $e^{i\pi} = -1$ ). Under this construction, both complex-valued rotation and higher-dimensional axis extension arise as different manifestations of the same underlying alignment process: one expressed as continuous phase transformation, and the other as expanded spatial embedding.

While spatial axes appear open-ended and unbounded, learners grounded in Infferus recognise that this apparent openness is itself a form of closure in reference. Metaphorically, the axis encodes both the smallest and largest scales of length within a single representation, such that its unbounded extension reflects a closed and self-consistent referencing of magnitude.

**Conversion from Matrix-Based Representations to GR Structures** The conversion from matrix-based representations to GR structure may be understood in two stages. First, the pure-length-contrast branching path structure associated with a square matrix is in principle directly resolvable through its eigen-structure or equivalent modal decomposition, although not uniquely, since multiple base references may realise the same underlying branch relations. These resolved branch relations can then be expressed as triangle alignments in a plane together with rotational extension, yielding a folded triangle bifurcation solution space whose local configurations are straightforward to construct. The non-trivial step is not the existence of such a realisation, but the fitting of a compact core GR structure to this folded branch space. In this sense, feasibility of conversion is not in doubt for a single matrix, while the main challenge lies in selecting a coherent and useful GR fit among multiple valid realisations.

This principle can be illustrated in the context of attention-based models. The latent inter-

action operator

$$K_{\text{latent}} = W_Q W_K^T$$

may be interpreted as a compressed structural representation whose modal decomposition provides a direct basis for constructing the core GR geometry through triangle bifurcation alignment. At the same time, the factorised form  $W_Q W_K^T$  retains directional information that is not explicit in the merged operator alone. In particular, the asymmetric roles of  $W_Q$  and  $W_K$  encode a directional diverge–converge structure, which can be used to resolve the orientation and flow of topological alignment within the reconstructed GR representation.

The extension to matrix multiplication follows the same structural principle. If two square matrices represent two branch structures, then their product corresponds to a directional diverge–converge composition in which the terminal branches of one structure are constrained to conform with the entry branches of the other. The resulting composed branch space may again be folded into a geometric realisation and fitted by a core GR structure together with recurrence and chaos degrees of freedom. In this process, the latent operator determines the geometric template, while its factorised components determine the directional topology of alignment.

**Reverse Mapping: From GR Structures to Matrix Representations.** The reverse mapping from GR structures to matrix-based representations follows a different complexity profile. While multiple GR configurations may correspond to similar matrix operators, the non-triviality in this direction arises from the need to select an appropriate encoding pathway rather than reconstruct structure. In practice, GR models can be directly trained through feedback processes, during which suitable matrix encodings are implicitly selected or constructed to support efficient execution.

Additional complexity emerges when attempting to merge multiple parallel GR chains into a single unified structure, particularly when these chains are associated with different feedback anchors. Such merging may be required prior to forming a single consolidated matrix representation, and is not always trivial. However, in many practical scenarios, this requirement can be reduced or avoided by adopting decision-tree-like processes, where separate GR chains are maintained and evaluated in parallel. This approach not only reduces the need for structural merging, but may also improve computational efficiency by operating on smaller, more focused matrix streams.

Overall, compared to matrix-to-GR reconstruction, the GR-to-matrix direction presents a

more structured design and decision process. As the system matures and expands in capability, direct feedback-driven encoding from GR structures into matrix representations is expected to provide a more streamlined and efficient pathway for practical application.

#### 4.4.2 Challenges and Opportunities

In general, the unified knowledge system re-enables direct human intellectual guidance in pattern discovery at scales traditionally dominated by data-driven approaches. In current large-scale data exploration, human contribution is largely indirect: effort is primarily directed toward acquiring, curating, and organising datasets, while the discovery of implicit patterns is delegated to computational models. As a result, human involvement in pattern formation is mediated and often inefficient at the structural level.

At the same time, many foundational patterns used in data-driven systems originate from human-generated sources, including language, art, and cultural constructs. As automated generation becomes increasingly efficient in routine tasks, the rate of novel human-generated pattern formation may decrease, leading to a plateau in the diversity and depth of patterns available for purely data-driven exploration. In this context, the unified knowledge system plays a critical role by restoring a direct pathway for structured human contribution to pattern discovery.

However, the development of such a system depends fundamentally on the effective education of its contributing community. The core architectural and representational principles described in this work require learners to develop structural intuition and alignment-based understanding, which serve as the primary source of high-quality pattern generation. Human consciousness, through replica tiering closure, remains the domain in which meaning is stabilised and interpreted; computational systems, including the unified knowledge system, act as partial loops that support and extend this process.

Consequently, the advancement of the unified knowledge system is not primarily constrained by data availability or computational capacity, but by the efficiency and effectiveness of its educational processes. The cultivation of structurally trained individuals—capable of navigating, constructing, and extending alignment-based representations—is essential for sustained growth in pattern exploration. Both data-integrated exploration and data-free generative discovery within the system ultimately depend on the contributions of such individuals, making education the central driver of long-term capability.

*The ultimate limit of pattern discovery is not determined by data,  
but by the depth of human structural understanding.*