The Information-Theoretic Geometry of Representation and Communication: Reality Compression Signatures

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Abstract

Many adaptive systems compress high–dimensional environmental information into tractable internal representations in order to support prediction and action under informational constraints. While information–theoretic approaches have studied how individual agents perform such compression, most models implicitly assume that interacting agents share a common representational space. In practice, different agents may compress the same environment through distinct representational architectures.

This paper develops the concept of *reality compression signatures* as a formal framework for characterizing how agents encode, preserve, and reconstruct environmental information under information–theoretic constraints. Each agent is modeled as possessing a compression signature that defines its encoding, decoding, and distortion tolerance. Distances between signatures induce a geometric structure in representation space that governs semantic interoperability between agents.

We formalize signature distance, decoding elasticity, and interoperability, and show how these mechanisms induce weighted communication networks whose connectivity depends on representational compatibility. As signature divergence increases relative to decoding elasticity, communication networks undergo fragmentation into clusters of representation-compatible agents.

This work establishes a formal basis for analyzing communication breakdown, intellectual fragmentation, and interoperability among heterogeneous cognitive and artificial systems.

Contents

1 Introduction

A central difficulty in modeling communication between heterogeneous agents is that different systems may compress the same environmental structure into fundamentally different representational architectures.

Cognitive and learning systems must transform high–dimensional environmental observations into tractable internal representations in order to support prediction and action under informational constraints. In both biological cognition and artificial learning systems, this process can be interpreted as a form of information compression: raw observations are mapped into latent representations that preserve predictive structure while reducing informational complexity.

Extensive work in information theory and cognitive science has studied how individual systems perform such compression. However, existing frameworks typically assume that agents operate within a shared representational space. In practice, different agents may compress the same environmental structure using distinct representational architectures. When these architectures diverge sufficiently, agents may no longer interpret encoded information in compatible ways.

As a consequence, agents interacting within the same environment may exhibit systematic differences in interpretation, inference, and communication. These differences are rarely modeled explicitly. Most theories of cognition and communication treat disagreement as occurring within a shared semantic framework. Yet in many settings the underlying representational structures themselves may differ, producing communication failure even when agents are exposed to identical information. This paper proposes a conceptual framework and research agenda.

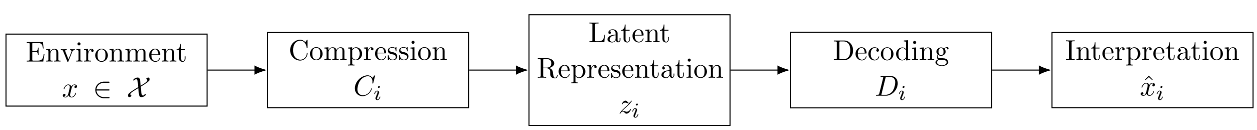


Figure 1: Environmental observations are compressed into latent representations and subsequently reconstructed through the agent's decoding architecture.

1.1 Compression and Model Formation

The interpretation of learning and model formation as compression of empirical structure has deep roots in information theory and cognitive science. In algorithmic information theory, the structure of a phenomenon is defined by the length of its shortest description. Similarly, the Minimum Description Length principle interprets model selection as identifying representations that compress observed data while preserving predictive structure.

In cognitive neuroscience, related ideas appear in theories of predictive processing, where perception and cognition are modeled as the construction of generative models that compress sensory input into latent representations capable of supporting prediction and inference.

Across these perspectives, compression plays a central role in the formation of internal models. However, existing frameworks primarily focus on compression within individual systems rather than differences between systems.

1.2 Representation Diversity

In real-world populations, agents rarely share identical representational structures. Differences in training data, prior assumptions, abstraction hierarchies, and distortion tolerances can produce distinct compression architectures even when agents observe the same environment.

These representational differences can manifest as several observable phenomena:

- persistent disagreement between agents
- communication breakdown across disciplines
- fragmentation of intellectual communities
- emergence of tightly connected epistemic clusters

Despite their prevalence, these phenomena are rarely modeled as consequences of representational compression differences.

1.3 Reality Compression Signatures

To address this gap, we introduce the concept of *reality compression signatures*. A reality compression signature characterizes the architecture through which an agent compresses, represents, and reconstructs environmental information.

We model each agent as possessing a signature that determines how observations are encoded into latent representations and how those representations are subsequently interpreted. Differences between agents can therefore be described as distances between compression signatures in representation space.

These distances have direct consequences for communication. When two agents possess similar signatures, information encoded by one agent can be decoded by the other with minimal distortion. As signatures diverge, semantic interoperability decreases, eventually leading to communication failure.

1.4 Core Concepts

The framework introduced in this paper is organized around five core concepts.

Concept	Description
Signature	Architecture through which an agent compresses and reconstructs reality
Distance	Divergence between compression signatures of two agents
Interoperability	Ability of one agent to decode representations produced by another
Elasticity	Range of signature distances over which decoding remains viable
Fragmentation	Emergence of clusters of representation-compatible agents

Together these concepts provide a minimal vocabulary for describing how differences in representational compression influence communication and network structure.

1.5 Contribution

This paper introduces the concept of reality compression signatures and develops a formal framework for modeling how differences in representational compression across agents shape semantic interoperability and communication structure.

Specifically, we formalize signature distance, decoding elasticity, and interoperability between agents, and we show how these mechanisms induce communication networks that fragment into clusters when signature divergence exceeds elasticity thresholds.

By modeling agents as heterogeneous compression systems, the framework provides a principled basis for analyzing communication breakdown, intellectual fragmentation, and the emergence of representation-compatible communities in cognitive and social systems.

The present work is intended as a conceptual and formal framework rather than an empirical model. Its purpose is to define a vocabulary and mathematical structure for analyzing communication between heterogeneous compression architectures. The framework therefore emphasizes definitional clarity and structural relationships rather than empirical validation. Empirical estimation of compression signatures and interoperability metrics is left to future work.

Scope of the Present Work The objective of this paper is to establish a conceptual and mathematical framework for analyzing communication between heterogeneous compression architectures. Accordingly, the emphasis is placed on definitional clarity and structural relationships, while empirical estimation and domain-specific validation of compression signatures are left to future work.

This paper introduces a formal framework in which communication between agents is modeled as an interaction between heterogeneous compression architectures operating on shared environmental observations.

2 Reality Compression Signatures

This section introduces the central object of the framework: the *reality compression signature*. The concept formalizes how different agents compress, represent, and reconstruct environmental information.

Cognitive and learning systems rarely operate directly on raw environmental observations. Instead, they construct internal representations that compress environmental structure into tractable models. These representations preserve information relevant for prediction and action while discarding information considered irrelevant or redundant.

Principle 1.
Agents do not interact with reality directly; they interact with compressed representations of reality.

Because compression necessarily discards information, different agents may construct different representations of the same environment. These representational differences form the basis of the framework introduced in this paper.

2.1 Environmental Observations

Let

$$x \in \mathcal{X}$$

denote observations drawn from an environment.

The observation space $\mathcal{X}$ may contain sensory measurements, linguistic inputs, or other informational structures available to the agent. In realistic settings this space is often extremely high dimensional.

Directly storing or reasoning over this raw space is typically infeasible. Instead, agents construct compressed representations that preserve relevant environmental structure.

2.2 Compression and Representation

We model each agent i as an information–processing system that compresses environmental observations into a latent representation space.

The compression process is defined by the mapping

$$C_i : \mathcal{X} \to \mathcal{Z}_i$$

where $\mathcal{Z}_i$ denotes the latent representation space of agent i.

These latent representations encode the internal structure through which the agent interprets environmental information. Because agents may differ in their abstraction hierarchies, priors, and objectives, the representation spaces $\mathcal{Z}_i$ may vary significantly across agents.

Compressed representations are interpreted through a decoding process

$$D_i : \mathcal{Z}_i \to \hat{\mathcal{X}}_i$$

where $\hat{\mathcal{X}}_i$ denotes the reconstructed interpretation of the observation.

Principle 2.
Compression defines the structure of an agent's internal representation of the world.

The pair (C_i, D_i) therefore describes how an agent transforms environmental information into internal representations and back again.

2.3 Definition of Reality Compression Signatures

We now define the formal object that captures this representational architecture.

Definition. The *reality compression signature* of agent i is the tuple

$$\Sigma_i = (\mathcal{Z}_i, C_i, D_i, L_i)$$

where

- $\mathcal{Z}_i$ is the latent representation space,
- C_i is the compression operator,
- D_i is the decoding operator,
- L_i is the distortion functional tolerated by the agent.

The distortion functional L_i determines which information losses are acceptable during compression. Different agents may tolerate different distortions depending on their objectives or representational constraints.

$$\boxed{x} \longrightarrow \boxed{C_i} \longrightarrow \boxed{z_i \in \mathcal{Z}_i} \longrightarrow \boxed{D_i} \longrightarrow \boxed{\hat{x}_i}$$

$$\Sigma_i = (\mathcal{Z}_i, C_i, D_i, L_i)$$

Figure 2: Structure of a reality compression signature. The signature defines the compression and decoding architecture used by an agent.

2.4 Interpretation

Reality compression signatures capture structural properties of representational architectures rather than specific beliefs.

Two agents may observe the same environmental observation x yet produce different latent representations:

$$C_i(x) \neq C_j(x)$$

even when exposed to identical information.

These differences arise from variations in abstraction structure, distortion tolerance, and representational objectives.

Principle 3.
Differences in compression architecture produce differences in interpretation.

Consequently, agents may disagree not only about conclusions but about how environmental information should be represented in the first place.

2.5 Components of a Compression Signature

The components of a reality compression signature are summarized below.

Component	Description
$\mathcal{Z}_i$	Latent representation space used by the agent
C_i	Compression operator mapping observations to representations
D_i	Decoding operator reconstructing interpretations
L_i	Distortion functional governing acceptable information loss

Together these components define the representational architecture through which an agent interacts with environmental information.

2.6 Representational Diversity

Reality compression signatures allow us to formalize representational diversity across agents.

Principle 4.
Agents observing the same environment may construct fundamentally different compressed representations of that environment.

This observation motivates the next section, where we introduce a distance metric between signatures and examine how representational differences influence communication between agents.

3 Signature Distance

Reality compression signatures describe how agents encode and interpret environmental information. Once these signatures are defined, the next step is to quantify how different two signatures are.

This section introduces a distance metric between signatures that captures divergence between representational architectures.

Principle 5.
Differences in interpretation arise from differences in compression architecture.

Two agents may observe identical environmental data while producing different internal representations. Signature distance formalizes this divergence.

3.1 Definition of Signature Distance

Let Σ_i and Σ_j denote the compression signatures of agents i and j.

We define the *signature distance*

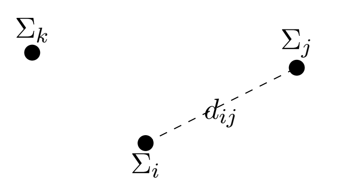
$$d_{ij} = d(\Sigma_i, \Sigma_j)$$

as a measure of divergence between the compression architectures of two agents.

Small values of d_{ij} indicate that agents compress and reconstruct environmental information in similar ways. Large values indicate that the agents rely on fundamentally different representational structures.

Principle 6.
Communication difficulty increases as compression signatures diverge.

This principle motivates the role of signature distance as a central quantity in the analysis of communication between agents.



Signature Space

Figure 3: Agents occupy positions in compression-signature space. Distances between signatures measure divergence in representational architecture.

Metric Structure of Signature Space The distance function $d(\Sigma_i, \Sigma_j)$ is assumed to define a metric over the space of compression signatures $\mathcal{S}$ such that

$$d(\Sigma_i, \Sigma_j) \geq 0$$

$$d(\Sigma_i, \Sigma_j) = 0 \iff \Sigma_i = \Sigma_j$$

$$d(\Sigma_i, \Sigma_j) = d(\Sigma_j, \Sigma_i)$$

$$d(\Sigma_i, \Sigma_k) \leq d(\Sigma_i, \Sigma_j) + d(\Sigma_j, \Sigma_k)$$

These properties allow the set of compression signatures to be interpreted as a geometric representation space in which interoperability relationships can be analyzed.

3.2 Components of Signature Distance

Because a compression signature contains multiple structural elements, the distance between signatures may depend on several factors.

Component	Source of Divergence
Representation space ($\mathcal{Z}_i$)	Differences in latent abstraction structure
Compression operator (C_i)	Differences in feature extraction and model structure
Decoding operator (D_i)	Differences in interpretation and reconstruction
Distortion functional (L_i)	Differences in tolerated information loss

Each of these components contributes to the overall divergence between signatures. In practice, the distance metric may aggregate these differences into a single scalar quantity.

3.3 Metric Structure

In general, the signature distance function may be treated as a metric over the space of compression signatures:

$$d(\Sigma_i, \Sigma_j) \geq 0$$

$$d(\Sigma_i, \Sigma_j) = d(\Sigma_j, \Sigma_i)$$

$$d(\Sigma_i, \Sigma_k) \leq d(\Sigma_i, \Sigma_j) + d(\Sigma_j, \Sigma_k)$$

These properties allow the collection of agents to be embedded in a metric representation space whose geometry reflects differences in compression architectures.

Within this space, agents with similar representational structures occupy nearby regions, while agents with fundamentally different compression architectures lie far apart.

3.4 Interpretation in Representation Space

The concept of signature distance allows us to interpret populations of agents geometrically.

Each agent occupies a position in a latent *signature space*, and the distance between agents reflects the divergence of their representational architectures.

Clusters of agents with small pairwise distances correspond to groups that compress environmental information in similar ways. Such clusters often correspond to:

- disciplinary communities
- epistemic traditions
- shared modeling frameworks

Conversely, large signature distances correspond to agents whose representations of the environment differ substantially.

Principle 7.
Representation similarity induces communication compatibility.

3.5 Implications for Communication

Signature distance plays a central role in determining whether information encoded by one agent can be decoded by another.

When d_{ij} is small, encoded information is likely to be interpreted similarly by both agents. As d_{ij} increases, decoding becomes increasingly difficult.

Beyond a critical divergence threshold, encoded signals may no longer be interpretable by the receiving agent. In such cases, communication failure occurs even when agents are exposed to identical observations.

These effects motivate the next section, where we formalize semantic interoperability and analyze how signature distance governs the success or failure of communication between agents.

4 Semantic Interoperability

Signature distance describes how representational architectures differ between agents. However, the central question for communication is not merely whether signatures differ, but whether the representations produced by one agent can be successfully interpreted by another.

To capture this property we introduce the concept of *semantic interoperability.*

> **Principle 8.**
> Communication succeeds when encoded representations can be decoded with minimal semantic distortion.

Semantic interoperability measures the degree to which information encoded by one agent remains interpretable when decoded by another.

4.1 Encoding and Decoding Across Agents

Consider two agents i and j with compression signatures Σ_i and Σ_j.

Agent i observes an environmental state $x \in \mathcal{X}$ and produces a compressed representation

$$z_i = C_i(x)$$

Agent j then attempts to decode this representation using its own decoding architecture

$$\hat{x}_j = D_j(z_i)$$

If the decoding process preserves the relevant structure of the original observation, the communication between the two agents is successful. Otherwise, information may be distorted, misinterpreted, or lost entirely.

> **Principle 9.**
> Successful communication requires compatibility between encoding and decoding architectures.

4.2 Formal Definition

We define semantic interoperability between agents i and j as

$$\mathcal{I}_{ij} = \mathbb{E}_{x \sim \mathcal{X}} \left[S(D_j(C_i(x)), x) \right]$$

where

- C_i is the compression operator of agent i,
- D_j is the decoding operator of agent j,
- $S(\cdot, \cdot)$ is a semantic similarity function,
- x is drawn from the environmental observation distribution.

The function $S(\cdot, \cdot)$ measures how closely the reconstructed interpretation $D_j(C_i(x))$ matches the original observation x in terms of semantic content.

$$\boxed{x} \longrightarrow \boxed{C_i} \longrightarrow \boxed{z_i} \longrightarrow \boxed{D_j} \longrightarrow \boxed{\hat{x}_j}$$

$$\mathcal{I}_{ij} = S(\hat{x}_j, x)$$

Figure 4: Cross-agent encoding and decoding. Agent i encodes an observation which agent j attempts to decode. Semantic interoperability measures how well the reconstructed interpretation matches the original observation.

Proposition 1 (Interoperability Decay)**.** *Let interoperability weights be defined by*

$$w_{ij} = \exp\left(-\frac{d_{ij}^2}{2\ell^2}\right).$$

Then interoperability decreases monotonically with increasing signature distance:

$$\frac{\partial w_{ij}}{\partial d_{ij}} < 0.$$

Proof. Differentiating,

$$\frac{\partial w_{ij}}{\partial d_{ij}} = -\frac{d_{ij}}{\ell^2} \exp\left(-\frac{d_{ij}^2}{2\ell^2}\right) < 0$$

for $d_{ij} > 0$. □

4.3 Interpretation

Semantic interoperability can be interpreted as the expected fidelity with which information survives cross-agent encoding and decoding.

Interoperability Level	Interpretation
High $\mathcal{I}_{ij}$	Representations decode with minimal distortion
Moderate $\mathcal{I}_{ij}$	Partial interpretation with semantic drift
Low $\mathcal{I}_{ij}$	Representations become uninterpretable

When interoperability is high, agents can exchange information efficiently even if their signatures differ slightly. As interoperability decreases, communication becomes increasingly fragile.

Principle 10.
Disagreement presupposes interoperability.

Two agents must first successfully decode each other's representations before they can meaningfully disagree about them.

4.4 Relationship to Signature Distance

Semantic interoperability depends strongly on signature distance. As the divergence between compression signatures increases, the probability that encoded information will be decoded correctly decreases.

In general we expect interoperability to decrease as signature distance increases:

$$\frac{d\mathcal{I}_{ij}}{dd_{ij}} < 0$$

where d_{ij} denotes signature distance.

Small signature distances therefore correspond to high semantic interoperability, while large distances lead to communication breakdown.

Principle 11.
Semantic interoperability decays as compression signatures diverge.

4.5 Communication Regimes

Combining signature distance with semantic interoperability allows us to identify three regimes of interaction between agents.

Signature Distance	Interoperability	Communication Regime
Small	High	Agreement or productive discussion
Moderate	Moderate	Disagreement with shared interpretation
Large	Low	Semantic invisibility or communication failure

The final regime corresponds to situations where encoded signals cannot be interpreted within the decoding architecture of the receiving agent.

Principle 12.
Communication failure occurs when signature distance exceeds decoding compatibility.

4.6 Implications for Communication Networks

Semantic interoperability provides the basis for defining communication networks among agents.

Edges between agents can be weighted by their interoperability

$$w_{ij} = \mathcal{I}_{ij}$$

which captures the probability that information exchanged between the agents will be interpreted correctly.

As signature divergence increases across a population, interoperability weights decrease, eventually leading to fragmentation of the communication network.

The next section introduces the concept of *elasticity*, which determines how much signature divergence an agent can tolerate before interoperability collapses.

5 Elasticity

Signature distance determines how different two representational architectures are, while semantic interoperability determines whether encoded information can be successfully decoded. However, agents may differ in how tolerant their decoding architectures are to representational divergence.

We refer to this tolerance as *elasticity*.

Principle 13.
Agents differ in how far their decoding architectures can stretch while preserving semantic interpretation.

Elasticity captures the range of compression signatures an agent can interpret before communication fails.

5.1 Definition

Let d_{ij} denote the signature distance between agents i and j, and let $\mathcal{I}_{ij}$ denote their semantic interoperability.

We define the *elasticity* of agent i as

$$E_i = \sup\{r : d(\Sigma_i, \Sigma_j) \leq r \Rightarrow \mathcal{I}_{ij} \geq \kappa\}$$

where κ is a minimum interoperability threshold.

Intuitively, elasticity defines the maximum representational divergence that an agent can tolerate while still decoding information successfully.

5.2 Interpretation

Elasticity describes how robust an agent's decoding architecture is to differences in representational compression.

Elasticity Level	Interpretation
Low elasticity	Only similar signatures can be decoded
Moderate elasticity	Compatible with several related representations
High elasticity	Capable of interpreting diverse compression structures

Agents with low elasticity require highly compatible representational structures in order to communicate successfully. Agents with high elasticity can interpret a wider range of compression architectures.

Principle 14.
Elasticity determines the tolerance of an agent to representational diversity.

5.3 Elasticity in Signature Space

The concept of elasticity can be visualized geometrically in signature space.

Each agent occupies a point in the latent space defined by compression signatures. Elasticity defines a neighborhood around that point within which other signatures remain interoperable.

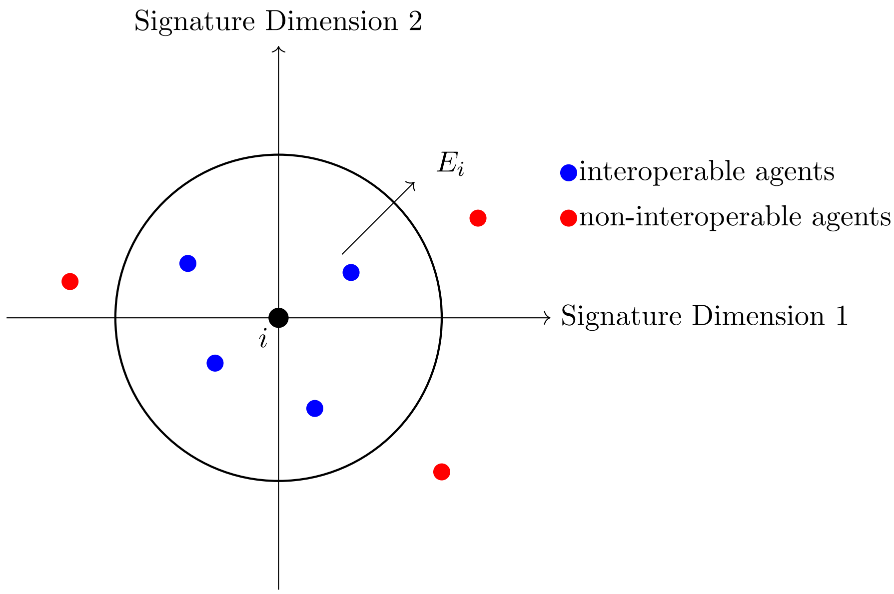


Figure 5: Elasticity radius in signature space. Agent i occupies a position in the latent compression-signature space. Agents whose signatures fall within the elasticity radius E_i can decode representations produced by agent i with interoperability above threshold κ. Agents outside this radius fall beyond the decoding tolerance of the agent, leading to communication failure.

Agents whose signatures lie within this radius can communicate successfully. Agents outside this radius fall beyond the decoding tolerance of the receiving agent.

Principle 15.
Communication remains viable only within an agent's elasticity radius.

5.4 Sources of Elasticity

Elasticity may arise from several structural properties of the agent's representational architecture.

Source	Effect on Elasticity
Flexible abstraction hierarchies	Increased representational tolerance
Robust decoding mechanisms	Improved cross-representation interpretation
Exposure to diverse training data	Broader decoding capability
Rigid modeling assumptions	Reduced representational tolerance

Agents trained across diverse informational environments may develop higher elasticity because their decoding architectures learn to interpret multiple representational forms.

5.5 Elasticity and Communication Stability

Elasticity plays a central role in determining the stability of communication networks.

When agents possess high elasticity, communication remains viable even when compression signatures diverge moderately. When elasticity is low, even small differences in representation may cause communication breakdown.

Principle 16.
Low elasticity amplifies the effects of signature divergence.

As a consequence, populations composed primarily of low-elasticity agents are more likely to fragment into isolated communication clusters.

5.6 Elasticity and Bridge Agents

Elasticity also explains the existence of agents capable of communicating across otherwise incompatible communities.

Agents with unusually high elasticity can interpret representations from multiple compression regimes, allowing them to act as bridges between clusters of otherwise incompatible signatures.

Agent Type	Role in Communication Networks
Low-elasticity agent	Communicates only within narrow clusters
Moderate-elasticity agent	Interacts with nearby signature communities
High-elasticity agent	Bridges multiple representation clusters

Such agents often play an important role in interdisciplinary communication and knowledge transfer.

Principle 17.
High-elasticity agents function as bridges between representational communities.

5.7 Implications for Network Fragmentation

Elasticity determines the range of signature distances over which communication remains viable. When signature divergence exceeds elasticity thresholds across a population, semantic interoperability collapses and communication networks fragment.

The next section examines how these dynamics produce large-scale fragmentation in communication networks.

6 Communication Networks

Reality compression signatures determine how agents encode and interpret environmental information. Signature distance quantifies divergence between representational architectures, while semantic interoperability determines whether encoded information can be successfully decoded across agents.

At the population level these pairwise interactions induce a communication network among agents.

Principle 18.
Communication networks emerge from compatibility between representational compression architectures.

In this section we formalize how interoperability between agents generates network structure.

6.1 Network Representation

Consider a population of agents

$$V = \{1, 2, \ldots, N\}$$

Each agent corresponds to a node in a communication network.

The resulting graph is

$$G = (V, E)$$

where edges represent successful semantic interoperability between agents.

Two agents may exchange information successfully if their compression signatures are sufficiently compatible.

6.2 Interoperability Kernel

To model the probability that two agents can interpret each other's representations, we introduce an interoperability kernel.

Let d_{ij} denote the signature distance between agents i and j. We define the interoperability weight

$$w_{ij} = \exp\left(-\frac{d_{ij}^2}{2\ell^2}\right)$$

where ℓ is an elasticity scale parameter.

Principle 19.
Communication strength decays as compression signatures diverge.

This kernel assigns high weight to agents with similar compression signatures and rapidly decreasing weight as representational divergence increases.

The Gaussian kernel is adopted as a smooth radial basis function modeling the decay of semantic interoperability with increasing representational divergence. This form ensures that small signature distances yield strong interoperability while large distances decay rapidly but continuously.

Theorem 1 (Elasticity-Limited Connectivity)**.** *Let interoperability weights be defined by*

$$w_{ij} = \exp\left(-\frac{d_{ij}^2}{2\ell^2}\right).$$

For any threshold $\tau \in (0, 1)$, an edge exists only if

$$d_{ij} \leq \ell\sqrt{-2\ln\tau}.$$

Thus, for fixed τ, communication connectivity is supported only within a finite radius in signature space.

Proof. If an edge is retained only when $w_{ij} \geq \tau$, then

$$\exp\left(-\frac{d_{ij}^2}{2\ell^2}\right) \geq \tau.$$

Taking logarithms gives

$$-\frac{d_{ij}^2}{2\ell^2} \geq \ln\tau,$$

which is equivalent to

$$d_{ij} \leq \ell\sqrt{-2\ln\tau}.$$

□

This result makes explicit that the interoperability kernel induces an effective communication radius in signature space, providing a geometric basis for cluster formation and network fragmentation.

6.3 Adjacency Matrix

The network structure can be represented by the weighted adjacency matrix

$$W = [w_{ij}]$$

where each element describes the strength of semantic interoperability between two agents.

Symbol	Description
V	set of agents (nodes)
E	communication edges
d_{ij}	signature distance between agents
w_{ij}	interoperability weight
ℓ	elasticity scale parameter
W	weighted adjacency matrix

The resulting graph is a weighted communication network whose structure reflects compatibility between compression signatures.

6.4 Geometric Interpretation

Because interoperability depends on signature distance, the resulting network can be interpreted as a geometric graph embedded in compression-signature space.

Agents located near each other in signature space form densely connected subnetworks, while agents with distant signatures exhibit weak or absent connections.

Principle 20.
Network connectivity reflects geometric proximity in signature space.

This structure naturally produces clusters of agents that share compatible representational architectures.

6.5 Network Structure

Several characteristic network structures emerge from this model.

Structure	Interpretation
Dense clusters	agents with highly compatible signatures
Sparse bridges	high-elasticity agents linking clusters
Weak long-range edges	partial representational compatibility
Disconnected components	incompatible compression architectures

Clusters often correspond to communities of agents that share similar abstraction hierarchies or modeling traditions.

6.6 Example Network Structure

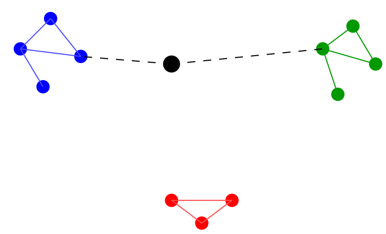


Figure 6: Example communication network induced by compression signature compatibility. Dense clusters correspond to groups of agents with similar signatures, while bridge agents enable limited interoperability between clusters.

6.7 Implications

The network model provides a structural view of communication among heterogeneous agents.

> **Principle 21.**
> Fragmentation occurs when signature divergence exceeds the interoperability range of the population.

As signature variance increases relative to the elasticity scale ℓ, interoperability weights decrease across the network. When these weights fall below a critical level, the communication graph breaks into disconnected components.

This phenomenon will be examined in the following section, where we analyze fragmentation dynamics in communication networks.

7 Network Fragmentation

The communication network introduced in the previous section emerges from pairwise semantic interoperability between agents. Because interoperability depends on compression signature distance, large-scale communication structure depends on the distribution of signatures within a population.

As representational divergence increases relative to the decoding tolerance of agents, interoperability decreases and the communication network may fragment into disconnected components.

> **Principle 22.**
> Communication networks fragment when representational divergence exceeds decoding tolerance.

This section formalizes the conditions under which such fragmentation occurs.

7.1 Control Parameter

To characterize the relationship between signature divergence and decoding tolerance, we introduce a dimensionless control parameter

$$\chi = \frac{\langle d_{ij} \rangle}{\ell}$$

where

- $\langle d_{ij} \rangle$ is the mean pairwise signature distance across the population
- ℓ is the elasticity scale governing interoperability decay

The parameter χ compares the typical representational divergence within the population to the decoding tolerance of agents.

Principle 23.
Network structure is governed by the ratio between representational diversity and decoding tolerance.

Small values of χ correspond to populations whose compression signatures remain within the interoperability range of most agents. Large values of χ correspond to populations with highly divergent representational architectures.

7.2 Regimes of Network Connectivity

Different regimes of communication structure emerge depending on the value of χ.

Control Parameter	Network Structure	Interpretation
$\chi \ll 1$	Dense network	High interoperability across agents
$\chi \approx 1$	Clustered network	Partial communication fragmentation
$\chi \gg 1$	Fragmented network	Isolated representational communities

When representational divergence remains small relative to elasticity, the network remains densely connected. As divergence increases, clusters of compatible signatures emerge. Beyond a critical range, communication between clusters becomes impossible.

7.3 Geometric Interpretation

Fragmentation can also be understood geometrically in compression-signature space.

Agents occupy positions in this latent space, and communication edges exist only when signature distances fall within the effective interoperability radius determined by elasticity.

Principle 24.
Clusters of communication correspond to regions of high signature density in representation space.

As signature variance increases, agents become more widely separated in signature space, reducing the number of edges that satisfy the interoperability condition.

7.4 Fragmentation Dynamics

The transition from a connected communication network to fragmented clusters can be visualized as follows.

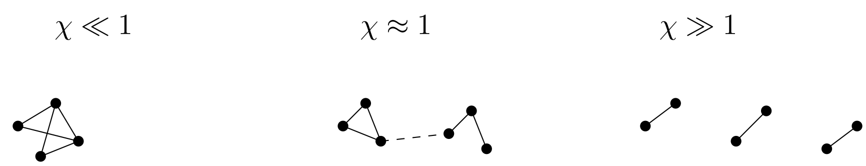


Figure 7: Illustration of communication network fragmentation as the control parameter χ increases. Left: dense connectivity when signature divergence is small. Middle: clustered network with weak inter-cluster communication. Right: fully fragmented network with isolated representational communities.

7.5 Implications

Network fragmentation reflects the emergence of communities whose representational compression architectures remain mutually compatible.

These clusters may correspond to:

- scientific disciplines
- intellectual traditions
- epistemic communities
- machine learning model families

Principle 25.
Intellectual communities emerge from compatibility between compression signatures.

From this perspective, fragmentation does not necessarily indicate disagreement. Rather, it reflects divergence in representational compression architectures.

When agents compress reality in incompatible ways, communication becomes impossible regardless of shared data or observations.

This interpretation reframes many forms of intellectual fragmentation as structural consequences of representational diversity rather than purely ideological conflict.

8 Conceptual Illustrations

8.1 Signature Space with Elasticity Radii

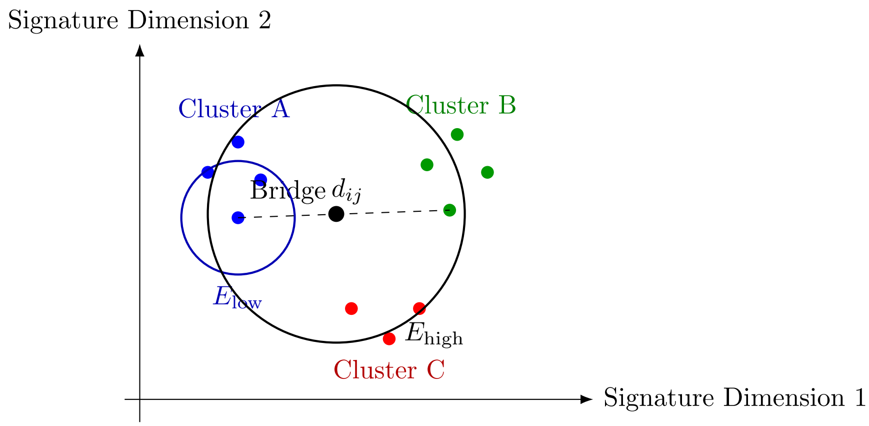


Figure 8: Agents embedded in compression-signature space. Pairwise distances correspond to divergence between representational architectures. Elasticity radii determine which agents remain semantically interoperable.

8.2 Agreement, Disagreement, and Semantic Invisibility

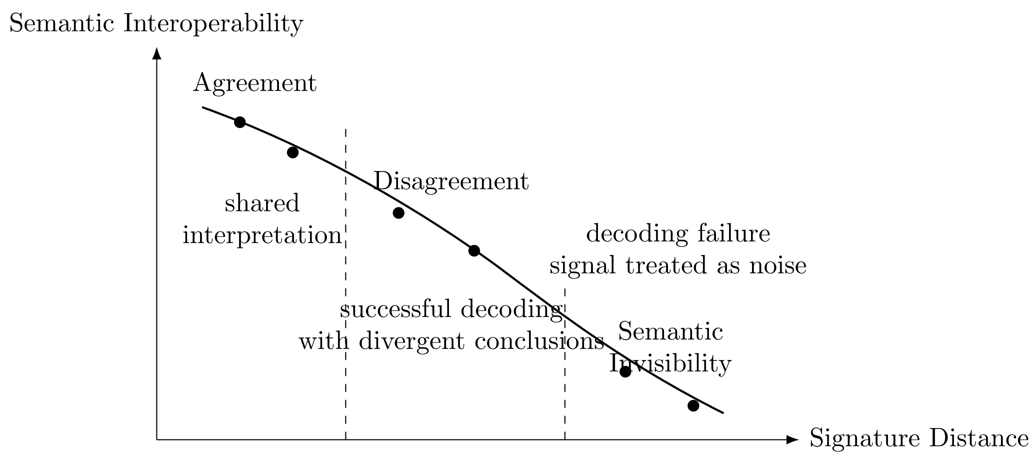


Figure 9: Communication regimes as a function of compression-signature distance. Small distances support shared interpretation, moderate distances permit disagreement within a shared semantic framework, and large distances produce semantic invisibility.

9 Limitations

The reality compression signature framework provides a conceptual and mathematical model for analyzing communication between heterogeneous complex adaptive systems. As with any abstract model, the framework relies on simplifying assumptions and idealizations.

The objective of this work is to establish a conceptual foundation; empirical measurement and validation of compression signatures remain open research problems.

This section clarifies the scope of the theory and identifies several limitations that should be addressed in future work.

Principle 29.
A model explains a phenomenon by isolating a subset of mechanisms while abstracting away others.

The present framework focuses specifically on representational compression and its implications for communication structure. Other mechanisms influencing communication dynamics fall outside the current model.

9.1 Representation-Centric Assumption

The framework assumes that communication success is determined primarily by compatibility between representational compression architectures.

In practice, communication outcomes may also depend on factors such as:

- shared vocabulary and language conventions
- institutional incentives
- social trust
- strategic communication behavior

These factors can influence communication even when compression signatures are compatible.

Principle 30.
Representational compatibility is a necessary but not sufficient condition for successful communication.

The present theory isolates representational structure as a primary explanatory variable but does not claim that it is the only determinant of communication dynamics.

9.2 Measurement of Compression Signatures

Another limitation concerns the practical estimation of compression signatures.

The framework defines signatures as

$$\Sigma_i = (\mathcal{Z}_i, C_i, D_i, L_i)$$

However, directly observing these components in real complex adaptive systems may be difficult. In empirical settings, signatures would need to be approximated using observable behavioral or representational data.

Potential proxies include:

- conceptual graphs extracted from text
- reasoning structures in explanations
- latent representations from machine learning models
- abstraction hierarchies inferred from discourse

Developing reliable empirical estimators of compression signatures remains an open research problem.

9.3 Choice of Distance Metric

The framework assumes that divergence between compression signatures can be represented by a distance function

$$d(\Sigma_i, \Sigma_j)$$

While this assumption provides useful mathematical structure, the specific form of the distance metric is not uniquely determined by the theory.

Different empirical contexts may require different distance measures depending on how compression architectures are represented.

Distance Type	Possible Interpretation
Representation-space distance	divergence in latent embeddings
Conceptual graph distance	structural differences in reasoning graphs
Model-parameter distance	differences between trained models
Information-theoretic divergence	differences in compression efficiency

Determining which distance metrics best capture representational divergence remains an important area for empirical validation.

9.4 Simplified Network Dynamics

The network model introduced in this paper assumes that communication edges are determined solely by pairwise interoperability.

In real communication systems, network dynamics may also depend on:

- historical interactions between agents
- reputation or authority effects
- institutional constraints
- evolving learning processes

The present model therefore represents a static approximation of communication structure rather than a full dynamic theory.

Principle 31.
Communication networks evolve over time as agents update their compression architectures.

Incorporating learning dynamics and adaptive compression remains an important direction for future research.

9.5 Population Homogeneity Assumptions

The theoretical analysis treats agents as possessing fixed elasticity parameters and compression signatures.

In real systems, these quantities may vary widely across individuals.

Agent Property	Possible Source of Variation
Elasticity	exposure to diverse representations
Compression architecture	training data and cognitive style
Decoding tolerance	prior modeling assumptions
Representation space	domain-specific expertise

Modeling heterogeneous populations more explicitly may yield richer network dynamics than those considered in the present analysis.

9.6 Conceptual Boundary of the Framework

The framework should not be interpreted as claiming that disagreement or fragmentation always arises from compression differences.

Rather, the theory proposes that representational divergence provides one structural mechanism capable of producing communication breakdown.

Principle 32.
The framework explains one mechanism of fragmentation, not all mechanisms.

Other explanations for communication failure may coexist with the representational mechanism proposed here.

9.7 Summary of Limitations

The major limitations of the present framework are summarized below.

Limitation	Description
Signature observability	compression signatures must be estimated indirectly
Metric specification	distance functions depend on empirical representation models
Static network model	communication dynamics are simplified
External influences	social and institutional factors not modeled
Population heterogeneity	variability in elasticity not fully explored

These limitations do not invalidate the framework but instead define a research agenda for future work.

9.8 Conceptual Scope

Figure 10 illustrates the conceptual scope of the framework.

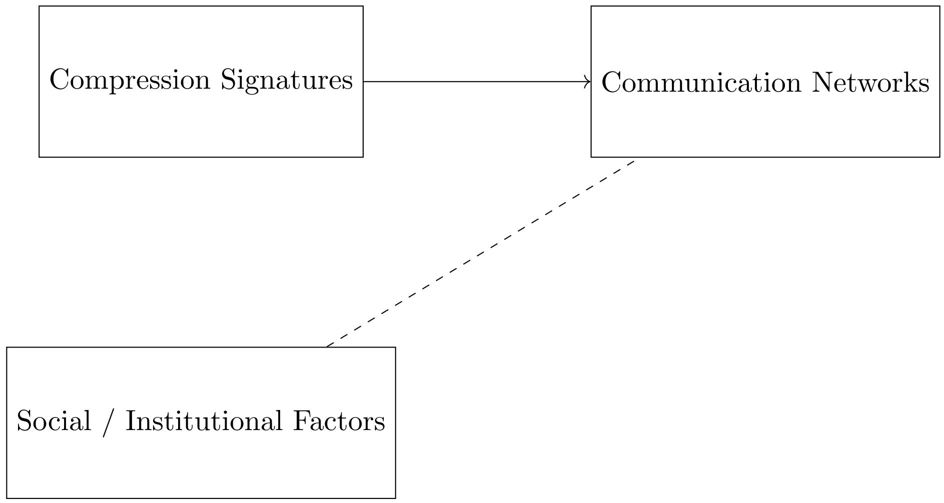


Figure 10: Conceptual scope of the framework. The theory focuses on how compression signatures shape communication networks, while acknowledging that additional external mechanisms may also influence communication dynamics.

Future work should explore how representational compression interacts with these additional mechanisms in shaping communication systems.

10 Discussion

The reality compression signature framework provides a structural perspective on communication dynamics among heterogeneous cognitive agents. The preceding sections formalized how representational compression architectures determine semantic interoperability and how divergence between these architectures can produce fragmentation in communication networks.

The central implication of the framework is that communication failure may arise not solely from disagreement in beliefs but from incompatibility between representational compression systems.

Principle 33.
Communication requires compatibility between representational compression architectures.

When compression signatures diverge beyond the decoding elasticity of agents, semantic interoperability collapses and communication networks fragment into clusters of representational compatibility.

10.1 Disagreement versus Invisibility

Traditional accounts of intellectual conflict often treat disagreement as the primary barrier to communication. In such models, agents share a common representational space but differ in conclusions or beliefs.

The present framework suggests an additional regime: semantic invisibility.

In this regime, agents do not merely disagree about interpretations; rather, they fail to interpret each other's representations at all.

Regime	Representational Compatibility	Communication Outcome
Agreement	High	Shared interpretation
Disagreement	Moderate	Divergent conclusions within a shared framework
Semantic invisibility	Low	Failure of decoding and interpretation

This distinction implies that disagreement presupposes interoperability. When interoperability collapses, disagreement itself becomes impossible.

Principle 34.
Disagreement requires shared representational structure.

The framework therefore distinguishes between debates that occur within a common conceptual space and communication failures that arise from incompatible compression architectures.

10.2 Intellectual Communities as Signature Clusters

The network model developed earlier suggests that clusters of agents with compatible compression signatures form naturally in representational space.

These clusters correspond to communities of agents capable of interpreting one another's representations with relatively low distortion.

Examples may include:

- scientific disciplines
- technical subfields
- intellectual traditions
- model families in machine learning

Principle 35.
Intellectual communities emerge from clusters of representational compatibility.

Within such communities, compression signatures remain sufficiently similar to permit high semantic interoperability. Communication across clusters becomes progressively more difficult as signature distance increases.

10.3 Role of High-Elasticity Agents

The concept of elasticity introduces the possibility of bridge agents capable of interpreting representations across multiple clusters.

Agents with high elasticity possess decoding architectures capable of accommodating a wider range of compression signatures.

These agents may play important roles in communication networks, including:

- interdisciplinary researchers
- translators between conceptual frameworks
- educators bridging multiple knowledge domains

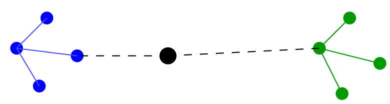
- generalist machine learning systems

Agent Type	Network Role
Low elasticity	local communication within clusters
Moderate elasticity	partial cross-cluster communication
High elasticity	bridging distinct representational communities

The presence or absence of such agents may significantly influence the connectivity of communication networks.

10.4 Geometric Interpretation of Communication Breakdown

The fragmentation process described earlier can be visualized geometrically in compression-signature space.



bridge agent

Figure 11: Communication clusters connected by a high-elasticity bridge agent. Without such agents, clusters become isolated components in the communication network.

In this representation, clusters correspond to dense regions of signature space where interoperability remains high. Bridge agents occupy positions enabling limited connectivity between otherwise separated regions.

10.5 Implications for Artificial Systems

The framework also has implications for artificial intelligence and machine learning systems.

Different models may learn distinct compression architectures even when trained on similar data. As a result, interoperability between models may depend on compatibility between their internal representations.

Possible applications include:

- analyzing interoperability between machine learning models
- measuring representational similarity across architectures
- designing systems capable of translating between model families

Principle 36.
Interoperability between intelligent systems depends on compatibility between learned compression architectures.

Understanding compression signature compatibility may therefore become increasingly important as heterogeneous artificial systems interact in shared environments.

10.6 Broader Interpretation

The framework suggests a broader interpretation of intellectual fragmentation.

Rather than viewing fragmentation solely as a consequence of disagreement or ideological conflict, the theory highlights representational divergence as a structural mechanism capable of producing communication breakdown.

In this view, fragmentation may reflect the natural emergence of clusters of agents who compress and interpret reality in compatible ways.

Communication breakdown is therefore not necessarily evidence of irrationality or hostility, but may instead arise from the geometry of representational compression within populations.

10.7 Research Directions

The framework introduced in this work is intended as a conceptual and formal foundation for analyzing communication between heterogeneous compression architectures. While the present paper focuses on defining the theoretical structure of reality compression signatures, several empirical research programs could explore how these concepts manifest in real systems.

- empirical estimation of compression signatures from observed data
- measurement of signature distance in cognitive and artificial systems
- analysis of interoperability across heterogeneous machine learning models
- dynamic models of evolving compression architectures
- empirical studies of fragmentation in communication networks

Developing methods for measuring compression signatures in real systems will be particularly important for validating the theory.

Neural Representation Analysis. One possible direction is the estimation of compression signatures from neural network representations. Latent embeddings produced by pretrained models provide a practical proxy for the representation space $\mathcal{Z}_i$. Distances between compression signatures could be estimated using representation similarity metrics such as centered kernel alignment (CKA), Procrustes alignment, or distributional divergences between embedding spaces. Such analyses could explore interoperability between models trained under different objectives or architectures.

Interoperability Across Artificial Systems. Another avenue is the study of interoperability across pretrained models. For example, representations generated by one model could be decoded or interpreted by another, providing empirical estimates of cross-model semantic interoperability $\mathcal{I}_{ij}$. This would allow investigation of how architectural or training differences influence the effective distance between compression signatures.

Scientific and Intellectual Networks. The framework may also be applied to knowledge networks. Citation graphs, topic embeddings, or conceptual graphs derived from scientific literature could be used to approximate representational structures of different research communities. Signature distances estimated from these representations could then be compared with observed patterns of citation, collaboration, or disciplinary fragmentation.

Human Communication Systems. Finally, discourse analysis and semantic network methods may provide proxies for compression signatures in human communication. Topic models, semantic embeddings, or conceptual graphs extracted from text corpora could be used to estimate representational divergence between communities, potentially linking signature distance to communication barriers observed in social or intellectual networks.

These directions illustrate how the theoretical framework introduced here may support empirical investigation across artificial intelligence, cognitive science, and social systems. The present work therefore aims to provide a conceptual and mathematical vocabulary that can guide future empirical studies of communication, interoperability, and fragmentation among heterogeneous representational systems.

The compression operators C_i may also be interpreted as agent-specific coarse-graining procedures that map high-dimensional environmental observations into lower-dimensional representational variables. In this sense, heterogeneous compression signatures can be viewed as alternative effective descriptions of the same underlying environment, analogous to coarse-grained representations that appear in statistical physics [14]. This perspective suggests that communication breakdown may arise when agents construct incompatible effective representations of shared observations.

11 Conclusion

This paper introduced the concept of *reality compression signatures* as a formal framework for understanding communication between heterogeneous cognitive agents.

The primary contribution of this work is the introduction of a conceptual and mathematical vocabulary for describing communication between heterogeneous compression architectures.

The framework is intentionally domain-agnostic so that it may be applied across cognitive science, artificial intelligence, and social systems.

The central idea is that agents do not interact directly with objective reality, but rather with compressed internal representations produced by their respective representational architectures. Differences in these architectures can produce systematic divergence in interpretation even when agents observe identical environmental data.

Principle 37.
Communication between agents depends on compatibility between their compression architectures.

By modeling agents as representational compression systems, the framework provides a geometric and network-theoretic perspective on communication dynamics.

11.1 Summary of the Framework

The theory developed in this paper is organized around five core concepts.

Concept	Role in the Framework
Reality Compression Signature	Representational architecture of an agent
Signature Distance	Divergence between compression architectures
Semantic Interoperability	Ability of one agent to decode another's representations
Elasticity	Tolerance of decoding architectures to representational divergence
Fragmentation	Emergence of communication clusters in networks

These concepts form a minimal vocabulary for analyzing how differences in representational compression shape communication networks.

11.2 From Compression to Communication Networks

The framework shows how representational compression produces network structure through a sequence of mechanisms.

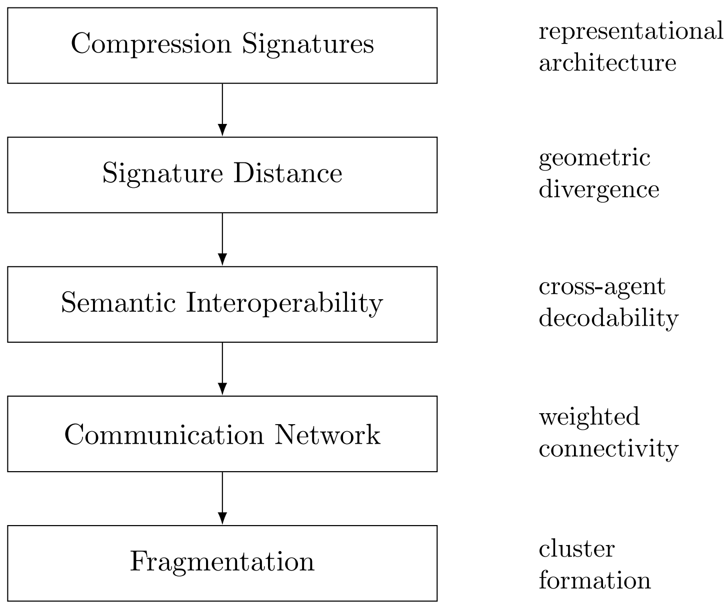


Figure 12: Schematic flow of the proposed framework. Differences in representational compression induce signature distances; these distances determine semantic interoperability, which shapes communication networks and their fragmentation into representationally compatible clusters.

This sequence provides a structural explanation for how heterogeneous complex adaptive systems produce clustered communication networks.

Principle 38.
Network fragmentation emerges from divergence in representational compression.

11.3 Implications

The framework provides a new perspective on several phenomena observed in intellectual and technological systems.

Phenomenon	Interpretation in the Framework
Scientific disciplines	clusters of compatible compression signatures
Interdisciplinary researchers	high-elasticity bridge agents
Communication breakdown	signature divergence beyond decoding tolerance
Intellectual fragmentation	network clustering in signature space

Rather than interpreting fragmentation solely as disagreement, the framework suggests that communication failure may arise from deeper divergence in representational compression architectures.

Principle 39.
Disagreement occurs within shared representation; fragmentation occurs when representation itself diverges.

11.4 Closing Perspective

The reality compression signature framework reframes communication as an interaction between representational architectures rather than merely an exchange of propositions or beliefs.

Principle 40.
Communication is the alignment of compressed representations of reality.

From this perspective, the structure of communication networks reflects the geometry of representational compression within populations of agents.

Understanding this geometry may provide new tools for analyzing intellectual fragmentation, improving communication across disciplinary boundaries, and designing interoperable artificial systems.

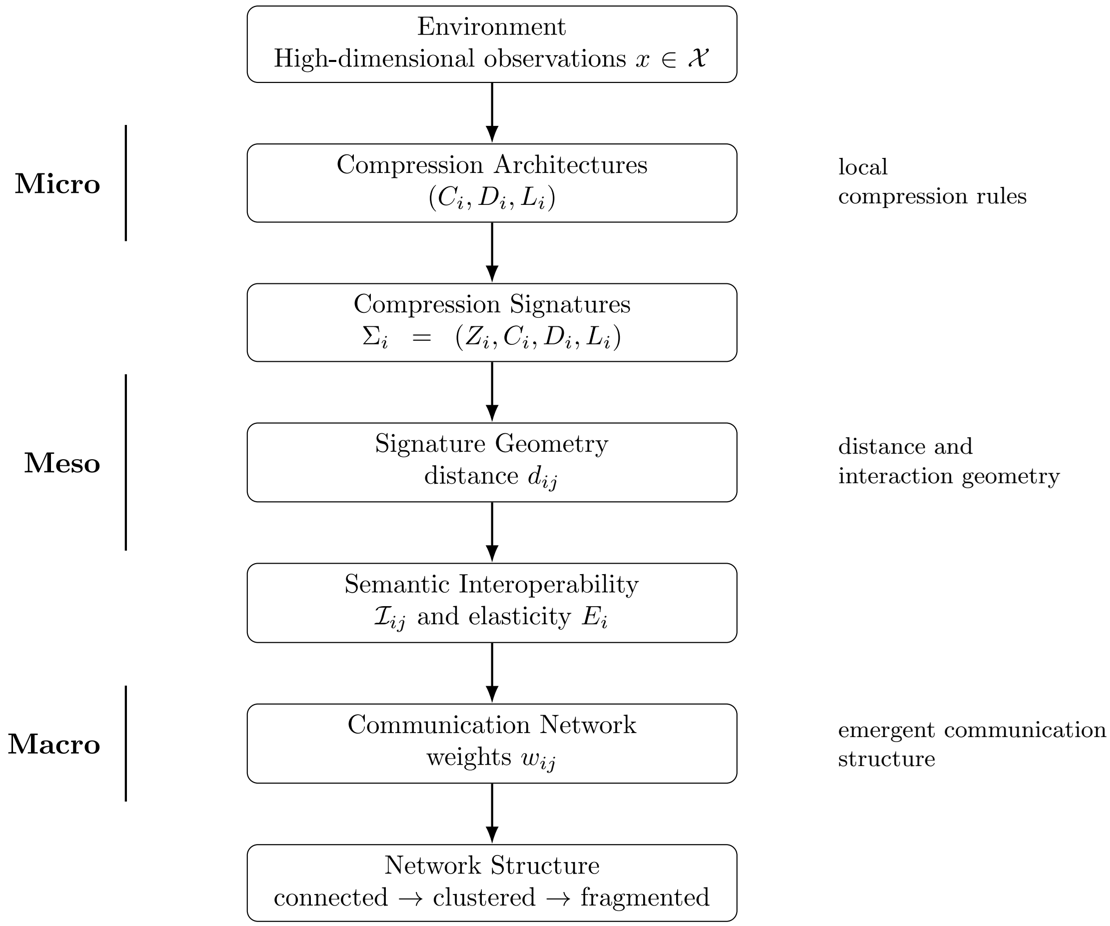


Figure 13: Multi-scale mechanism linking representational compression to large-scale communication structure. At the micro level, agents compress environmental observations through heterogeneous compression architectures. At the meso level, these architectures induce compression signatures, signature geometry, and semantic interoperability relations. At the macro level, these relations generate communication networks whose connectivity structure ranges from dense integration to clustered or fragmented communities of representational compatibility.

A Theory Skeleton

The theoretical structure of the framework can be summarized as follows.

Reality compression signatures

$$\Sigma_i = (\mathcal{Z}_i, C_i, D_i, L_i)$$

Signature distance

$$d_{ij} = d(\Sigma_i, \Sigma_j)$$

Interoperability

$$\mathcal{I}_{ij} = \mathbb{E}[S(D_j(C_i(x)), x)]$$

Elasticity

$$E_i = \sup\{r : d_{ij} \leq r \Rightarrow \mathcal{I}_{ij} \geq \kappa\}$$

Network interaction kernel

$$w_{ij} = \exp\left(-\frac{d_{ij}^2}{2\ell^2}\right)$$

Control parameter

$$\chi = \frac{\langle d_{ij} \rangle}{\ell}$$

Fragmentation emerges as χ increases beyond a critical range.

B Figure Summary

B.1 Signature Space

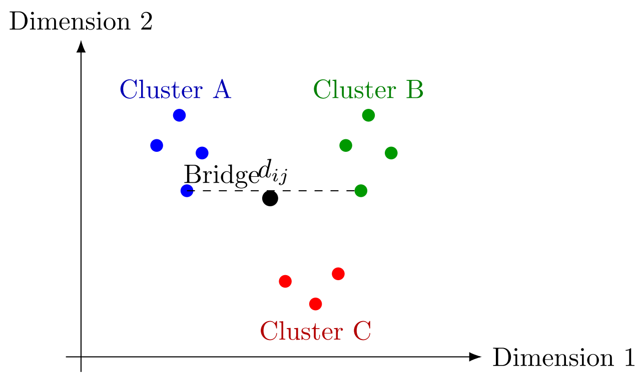


Figure 14: Agents as points in a latent signature space. Pairwise distance d_{ij} measures divergence between reality compression signatures. Dense regions correspond to clusters of agents with similar representational architectures.

B.2 Elasticity in Signature Space

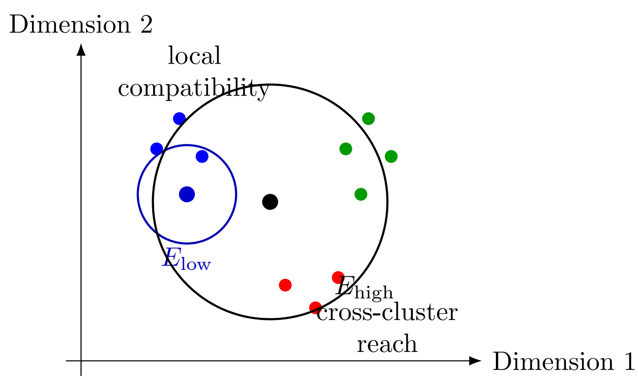


Figure 15: Elasticity defines the range of signature distances over which semantic interoperability remains viable. Low-elasticity agents communicate locally, whereas high-elasticity agents can bridge otherwise separated representational clusters.

B.3 Communication Network and Fragmentation

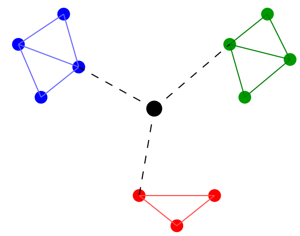


Figure 16: Communication network induced by signature compatibility. Dense intra-cluster connectivity emerges among agents with similar compression signatures, while inter-cluster communication is weak and often depends on high-elasticity bridge agents.

C Principles of Reality Compression Signatures

This appendix summarizes the conceptual principles underlying the framework introduced in the main text. These principles describe how heterogeneous compression architectures give rise to interoperability, communication structure, and network fragmentation.

C.1 Compression and Representation

1. All cognitive and artificial agents compress environmental information into internal representations in order to support prediction and action.
2. Compression reduces environmental complexity by mapping high-dimensional observations into lower-dimensional latent representations.
3. The structure of a representation reflects the inductive biases and distortion tolerances of the compression architecture that generated it.
4. Different agents may compress the same environmental structure in different ways.
5. Representations therefore depend not only on the environment but also on the compression architecture of the agent.
6. Compression signatures characterize the architecture through which agents encode and reconstruct environmental information.
7. A compression signature summarizes the representational geometry induced by an agent's encoding and decoding operators.
8. Compression signatures provide a formal description of how agents structure their internal representations of reality.

C.2 Signature Geometry

9. Differences between agents can be represented as distances between compression signatures.
10. Signature distance measures divergence between representational architectures rather than disagreement in beliefs.
11. Small signature distances correspond to similar representational structures.
12. Large signature distances correspond to incompatible compression architectures.
13. Signature distance induces a geometric representation space over the set of compression architectures.
14. Communication between agents depends on the relative position of their compression signatures within this space.
15. Representational geometry therefore constrains communication structure.
16. Agents with nearby compression signatures are more likely to interpret each other successfully.

C.3 Interoperability

17. Semantic interoperability describes the ability of one agent to decode representations generated by another.
18. Interoperability depends on the compatibility of compression signatures.
19. Successful communication requires that encoded representations remain interpretable under the decoding architecture of the receiving agent.
20. Cross-decoding failure occurs when representational divergence exceeds the tolerance of the decoding architecture.
21. Communication failure may therefore arise from incompatible compression architectures rather than disagreement about content.
22. Agents may partially interpret each other even when compression signatures differ.
23. Degrees of interoperability can therefore vary continuously across signature space.
24. Communication quality decreases as signature distance increases.

C.4 Elasticity

25. Elasticity describes the range of signature distances over which an agent can successfully interpret external representations.
26. Agents with high elasticity can interpret a wider range of compression architectures.
27. Agents with low elasticity are restricted to interpreting signatures very similar to their own.
28. Elasticity therefore determines the tolerance of an agent's decoding architecture to representational divergence.
29. Differences in elasticity influence communication structure within a population.
30. High-elasticity agents may act as bridges between otherwise incompatible representational communities.
31. Low-elasticity agents contribute to fragmentation by restricting interoperability.
32. Elasticity therefore plays a key role in shaping communication networks.

C.5 Network Structure and Fragmentation

33. Populations of agents interacting through communication form networks of semantic interoperability.
34. Network edges correspond to successful cross-decoding between agents.
35. Interoperability weights typically decrease as signature distance increases.
36. Distance-dependent interaction rules induce geometric communication networks.
37. As representational divergence increases, interoperability across the network decreases.

38. When signature divergence exceeds typical elasticity, communication links disappear.
39. This process leads to the formation of clusters of mutually interpretable agents.
40. Large populations may therefore fragment into multiple communities of representational compatibility.

C.6 Implications

The framework developed in this work suggests that large–scale patterns of communication may arise from structural differences in how agents compress and represent environmental information. When compression signatures remain sufficiently similar, semantic interoperability is preserved and communication networks remain densely connected. As representational divergence increases, interoperability decreases and communication links weaken, eventually producing clusters of mutually interpretable agents.

From this perspective, intellectual communities, disciplinary boundaries, and communication breakdowns may emerge naturally from the geometry of compression signatures in representation space rather than solely from differences in beliefs or intentions.

Conceptual Implications

Two general observations follow from this framework.

> Disagreement occurs when agents share a sufficiently similar representational structure to interpret each other's signals but reach different conclusions within that shared representation.
>
> Fragmentation occurs when representational structures themselves diverge to the point that signals produced by one agent can no longer be reliably interpreted by another.

Summary

The framework can be summarized as a structural progression:

Compression Architectures $\rightarrow$ Signature Geometry $\rightarrow$ Semantic Interoperability $\rightarrow$ Communication Networks $\rightarrow$ F

This progression provides a unified conceptual framework for analyzing communication among heterogeneous cognitive and artificial agents.

D Phase Diagram Interpretation

The network fragmentation dynamics described in Section 7 can be interpreted using a phase–diagram perspective common in statistical physics and complex systems theory.

Recall the control parameter introduced earlier:

$$\chi = \frac{\langle d_{ij} \rangle}{\ell}$$

where

- $\langle d_{ij} \rangle$ denotes the mean signature distance across the population
- ℓ represents the elasticity scale governing interoperability decay

This parameter compares the typical divergence between compression signatures to the decoding tolerance of agents.

The quantity S therefore acts as an order parameter for the connectivity of the communication network, analogous to order parameters used in percolation theory and statistical physics.

Small values of χ correspond to populations whose representational compression architectures remain mutually interpretable, while large values correspond to populations whose signatures diverge beyond decoding tolerance.

To characterize the connectivity transition more formally, consider the normalized size of the largest connected communication component

$$S = \frac{|C_{\max}|}{N}$$

where

- $|C_{\max}|$ is the size of the largest connected component
- N is the total number of agents

The quantity S acts as an **order parameter** describing the connectivity of the communication network.

Regime	Control Parameter	Network Structure
Connected	$\chi \ll 1$	Large connected communication component
Clustered	$\chi \approx 1$	Partial fragmentation with weak bridges
Fragmented	$\chi \gg 1$	Multiple disconnected communication clusters

From a conceptual perspective, the same regimes can be summarized as:

Control Parameter	Network Regime
$\chi \ll 1$	Dense connectivity with high semantic interoperability
$\chi \approx 1$	Clustered communication with weak inter-cluster bridges
$\chi \gg 1$	Fragmented network of isolated representational communities

These regimes resemble phase transitions in complex systems where a control parameter governs large-scale structural behavior.

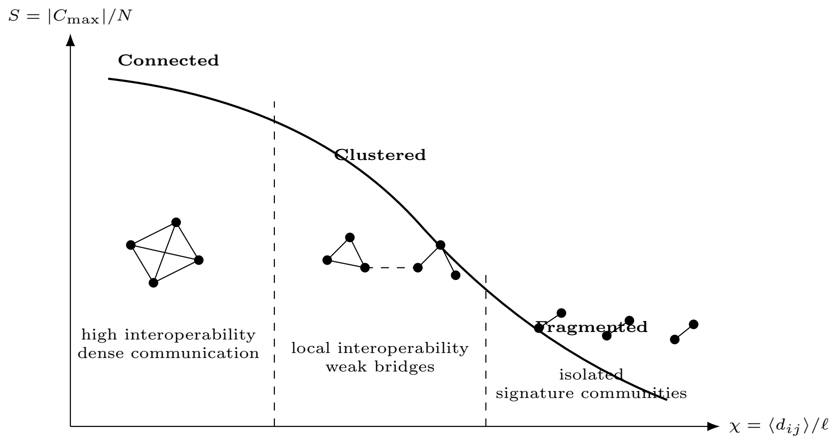


Figure 17: Phase-style statistical interpretation of communication structure as a function of the control parameter $\chi = \langle d_{ij} \rangle / \ell$, which compares mean signature divergence to decoding elasticity. The normalized size of the largest connected component $S = |C_{\max}|/N$ acts as an order parameter describing network connectivity. Small χ yields a densely connected communication regime, intermediate χ produces clustered networks with weak inter-cluster bridges, and large χ yields fragmentation into isolated communities of representational compatibility.

This phase-style interpretation highlights that communication fragmentation can emerge as a structural consequence of increasing representational divergence relative to decoding tolerance within a population.

In this perspective, intellectual communities, disciplinary boundaries, and communication breakdowns can be interpreted as structural consequences of the geometry of compression signatures in representation space. As representational divergence increases relative to decoding elasticity, the communication network undergoes a connectivity transition in which previously interoperable agents separate into clusters of mutually interpretable signatures. This behavior is analogous to connectivity phenomena studied in random geometric graphs and percolation models of complex networks, where large-scale network structure emerges from distance-dependent interaction rules [12, 13].

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