

The Signals Framework: A Semiotic Model for Emergent Participation in Decentralized Networks

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Abstract

This paper introduces the *Signals Framework*, a novel model for evaluating participation, influence, and alignment within decentralized networks. In contrast to point-based reputation systems, the framework treats signals as semiotic expressions, subject to contextual interpretation and recursive valuation. The model integrates graph-theoretic reasoning and trust propagation to produce a flexible and extensible foundation for incentivizing meaningful behavior in open, emergent communities. We further extend the framework with a modular signal analyzer architecture that allow actors within the ecosystem to interpret signals in their own way. Applications range from airdrop design to contributor reputation, cultural alignment, and governance. The Signals Framework offers a generalizable infrastructure for network-native legitimacy, enabling communities to bootstrap coherence, evolve values, and reward the unseen architecture of coordination.

1 Motivation and Conceptual Foundation

The Signals Framework is motivated by questions that are foundational to decentralized coordination: How can a network bootstrap meaningful participation? What mechanisms cultivate sustained engagement beyond purely economic incentives? And can a system be designed to be *autopoietic*, or in other words, how can we design it such that it's capable of generating and maintaining its own structure through internal feedback loops [1]?

These concerns are particularly relevant in the context of emerging organizational forms such as the *network state* [2, 3], in which communities formed around shared values and protocols may instantiate novel forms of sovereignty. In contrast to centralized platforms or extractive marketplaces, such communities require various forms of infrastructure that support trust, alignment, and coherence over time.

Prior research in commons governance highlights the role of localized trust, social norms, and collective reputation [4]. However, as Vitalik points out: the scarcest resource in network formation is not capital or computation but *legitimacy*, the shared belief that a system is worth participating in [5].

The Signals Framework addresses this challenge by introducing an infrastructure that enables participant-generated actions, referred to as *signals*, to be recognized, interpreted, and recursively valued within the network. Rather than imposing predefined metrics or prescriptive roles, the framework facilitates organic value emergence through context-sensitive interpretation.

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2 Signals as Mechanisms of Contribution and Coordination

A *signal* is any participant-generated action or artifact that others interpret as meaningful, such as publishing a guide, mentoring, referring a peer, launching a token, or creating cultural content. Signals are not statically defined, rather their meaning accrues through network interpretation, symbolic context, and social response, inspired largely by semiotic theory [6].

At a high level, signals serve multiple overlapping functions:

- **Feedback:** They reflect participant contributions back to both individual actors and the network, providing a sense of identity, tenure, and belonging.
- **Discovery:** They serve as beacons of intent, allowing others to identify aligned collaborators, mentors, or peers.
- **Growth:** They catalyze the network’s organic expansion by embedding contributions within visible, interpretable, and compounding structures.

Because signals are recursively valued (see subsection 6.3), early contributions can yield greater influence over time. For example, a participant who helps onboard a future project leader or initiates a long-lasting governance norm accrues recursive credit as that influence propagates.

Signals are not limited to any definitive fixed set of signal types. The framework supports an open, evolving taxonomy of signal types, from the operational (like completing a task) to the symbolic (like creating a meme, attending an event). Some signals, such as introductions that lead to further contributions, carry compounding effects. These may include:

- Introducing new participants who themselves become contributors
- Creating or curating knowledge that improves onboarding or coordination
- Facilitating connections that result in new projects, agreements, or other artifacts

By eschewing static point-based systems in favor of interpretive flexibility, the Signals Framework embeds evolving incentive gradients that reflect emergent community priorities. This design draws from research on complex adaptive systems [7, 8], where localized feedback loops give rise to global coherence.

Finally, the framework introduces a recursive mathematical model for signal *strength*, allowing contributions to gain recognition through downstream impact. This model, described in section 6, can be implemented via modular interpretants or *lenses*, each reflecting a distinct value logic (economic, cultural, governance etc.). The framework thus serves as a generalizable substrate for meaningful coordination in decentralized ecosystems.

3 Signals as Semiotic Expressions

Beyond their functional role in network coordination, signals are also *symbolic* acts insofar as they carry meaning that is shaped by context, intent, and interpretation. Drawing from the field of semiotics, the Signals Framework understands each signal not merely as data, but as a *sign* in the Peircean sense: a form that conveys meaning to an interpreter through a process of recognition and association [6].

In this formulation, a signal has three components:

- **Signifier:** The form the signal takes (e.g. a post, a referral, a meme, or a smart contract interaction).
- **Signified:** The underlying intent, value, or alignment it is meant to express (e.g. support, collaboration, critique, or affiliation).
- **Interpretant:** The understanding or response the signal produces in others, in individuals, algorithms, or the broader network.

This triadic structure allows signals to operate across multiple layers of meaning simultaneously. A signal may be interpreted differently by heterogeneous actors within the network (community manager, founders, investors etc.), supporting broad pluralism in interpretation.

Different modules, referred to as *lenses*, can be layered on top of the raw signal graph to produce different evaluative or interpretive outputs. A lens may prioritize economic participation, cultural fluency, coordination alignment, or any other chosen axis of value.

This approach aligns with work in applied semiotics and reflects the core principle that meaning is not inherent, but emerges through context and participation. In this way, signals serve both as informational primitives and symbolic infrastructure, encoding and enacting the shared reality of the network.

4 Signal Value and Signal Strength

Not all signals carry equal weight. While all contribute to the visibility and growth of the network, some require significantly more effort, skill, or commitment. Accordingly, the Signals Framework distinguishes between the *presence* of a signal and its *strength*—a scalar that reflects the depth, rarity, and downstream impact of that signal.

The concept of signal strength arises from several foundational observations:

- Actions differ in effort and complexity. Referring a new participant is valuable, but authoring a comprehensive explainer or mentoring a project team generally demands more time and contextual understanding.
- Contributions differ in rarity. A commonly repeated action (e.g. retweeting) should not carry the same systemic weight as a novel or high-effort contribution, especially when the latter sparks additional network effects.
- Influence can compound over time. A single meaningful action, such as onboarding a future founder, may continue to generate downstream effects long after the initial signal was emitted.

To account for these variations, the framework avoids the use of fixed-point systems. There are no predetermined scores like “10 points for a retweet” or “30 points for a referral”. Instead, signal strength is treated as a dynamic property, derived through a combination of intrinsic value, frequency-adjusted diminishing returns, participant credibility, and recursive propagation.

This design aligns with the principle of *value emergence*, the idea that the worth of an action should arise from how it interacts with the broader system, not from a top-down assignment. In particular, we are concerned with identifying and reinforcing signals that generate *network effects*, i.e. signals that result in new connections, collaborations, or transactions among participants [9].

This leads us to a core design distinction:

Signals are not static points. They are dynamic, semiotic expressions of participation. Their strength is determined not only by what was done, but also by how others respond.

In practice, signal strength is computed via a formal model (see section 6), but this model is itself interpretive. It provides one way of assigning operational value to participant activity. As with any metric, it is both a measurement and a *lens*, i.e. useful for some evaluative tasks, but not intended to fully replace human or community interpretation.

5 Signal-to-Noise Ratio

In any participatory system, especially one built around open signaling, the challenge arises of distinguishing meaningful contributions from superficial activity. As the network scales, the volume of emitted signals increases, but not all of them are equally valuable. Some may reflect deep engagement and long-term impact, while others may simply mirror opportunistic or low-effort behavior.

To address this, the Signals Framework introduces the concept of a *Signal-to-Noise Ratio* (SNR) as a contextual measure of signal quality. Inspired by information theory and adapted for decentralized social systems, SNR allows the network to detect which signals are genuinely contributing to its growth and coherence, and which are merely saturating the system without lasting impact.

Formally, the SNR of a signal type θ at time t can be expressed as a function of its cumulative rarity and observed downstream utility. In simplified terms:

$$\text{SNR}(\theta, t) = \frac{v_\theta}{1 + \lambda \cdot M_{\theta,t}} \quad (1)$$

Where:

- v_θ is the intrinsic value coefficient of the signal type.
- $M_{\theta,t}$ is the number of times the signal type θ has been emitted before time t .
- λ is a tunable decay parameter controlling how quickly marginal value diminishes.

This formulation reflects the principle that rarer or more high effort signals should carry more weight than more ubiquitous or easily replicable ones. Importantly, it does this without explicitly excluding any signal types, preserving expressive freedom while allowing the system to contextually favor behaviors that have higher overall impact.

Illustrative Example. Consider two participants: one refers ten new members in the earliest phase of the network (when such activity is rare), the other refers ten members at a time when the network has already grown substantially. Though both actions may be identical in form, their relative SNRs differ. The former has a much higher ratio because it occurs under conditions of scarcity and has a larger effect on network size, thereby qualifying as a stronger signal.

As the system matures, this dynamic allows for emergent filtering. Signals that are spammed or overused will, by design, have a low SNR and thus contribute less to overall signal strength. Conversely, signals that stand out in terms of initiative, timing, or compounding effects, retain a higher ratio and are more likely to propagate value upstream through recursive influence.

This approach aligns with work on attention filtering in social systems [7, 10] and addresses the need to cut through the noise in large, open networks [11].

6 Model for Calculating Signal Strength

This section presents a formal model for computing signal strength within decentralized networks. We construct the model incrementally, with each component introduced in sequence, building progressively toward the complete formulation in order to expound its overall design.

Throughout this section we refer to a running example: Alice publishes an on-boarding guide (a content signal), which inspires Bob to host mentorship sessions (a relational signal), which in turn enables Charlie to launch a project and publish a cultural artifact (productive and symbolic signals). This cascading sequence illustrates how contributions accrue meaning recursively.

6.1 Signal as a Tuple

Each signal σ is defined as:

$$\sigma = (a, t, \theta, \kappa, \pi)$$

Where:

- a : the actor (participant) emitting the signal
- t : the timestamp of the signal
- θ : the signal type (e.g., referral, content creation, agreement)
- κ : contextual metadata describing the signal’s content or context
- π : a provenance pointer referencing the upstream signal (if any)

Let Σ be the set of all signals, and $\Sigma_a \subset \Sigma$ be the subset emitted by actor a .

6.2 Base Signal Strength

Each signal type θ has an associated base strength defined by a diminishing returns function (aka Signal-to-Noise Ratio):

$$\alpha(\theta, t) = \frac{v_\theta}{1 + \lambda \cdot M_{\theta, t}}$$

Where:

- v_θ : intrinsic value coefficient for signal type θ
- $M_{\theta, t}$: number of prior signals of type θ before time t
- λ : decay factor, a tunable diminishing returns parameter

This mechanism ensures that early contributions receive greater weight while preserving value for repeated actions. For example, Alice’s onboarding guide, being one of the first of its type, has a high base strength. Later contributions of the same type must provide novelty to maintain comparable strength. The base signal strength is calculated for each signal type, and is updated any time a signal of that type is emitted.

6.3 Recursive Impact Modifier

While the base signal strength $\alpha(\theta, t)$ captures the immediate value of a signal, it does not reflect the broader consequences that signal may catalyze within the network. To account for this dynamic, we introduce the recursive feedback term $\beta(\kappa)$, which adjusts the signal’s valuation in accordance with its downstream impact. For instance, if a participant emits a signal—such as referring a new contributor—and that individual subsequently mentors others, initiates projects, or plays a foundational role in community growth, the initiating signal should proportionally increase in strength to reflect its sustained generative effect.

The recursive feedback modifier $\beta(\kappa)$ is defined as:

$$\beta(\kappa) = 1 + \sum_{\sigma' \in C(\sigma)} f(d(\sigma, \sigma')) \cdot S(\sigma') \quad \text{with} \quad f(d) = \lambda^d$$

- $C(\sigma)$: The set of causal descendants of signal σ
- $S(\sigma')$: The signal strength of each descendant σ'
- $d(\sigma, \sigma')$: The causal distance between σ and σ' (number of hops along the signal graph).
- $f(d) = \lambda^d$: A geometric decay function that reduces influence with depth.

Bob’s mentorship activities are triggered by Alice’s content. Charlie’s contributions build on Bob’s. These downstream effects feed back recursively to increase the effective strength of Alice’s original guide.

6.4 Depth Threshold

While the recursive feedback term $\beta(\kappa)$ rewards downstream influence, allowing it to recurse indefinitely introduces risk of signal runaway where a single signal benefits disproportionately from a large, deep causal tree. To control this, we introduce a depth threshold, denoted d_{max} , which limits how far influence is allowed to propagate. Any descendant signal beyond this maximum causal distance is ignored.

This is represented in the formula by an indicator function $\mathbb{I}[\cdot]$, which evaluates to 1 if a descendant is within the depth limit and 0 otherwise.

$$\beta(\kappa) = 1 + \sum_{\sigma' \in C(\sigma)} \mathbb{I}[d(\sigma, \sigma') \leq d_{max}] \cdot f(d(\sigma, \sigma')) \cdot S(\sigma')$$

This ensures Alice receives credit for near-term outcomes such as Charlie’s contributions, but not for distant, unrelated activities that are much further along the signal graph.

6.5 Normalization Across Descendants

Even with a depth constraint in place, a single signal may still accrue disproportionate influence if it resides at the root of a highly branched causal subtree. In such cases, the aggregated strength of numerous descendant signals, even within the permitted depth, can significantly inflate the upstream signal’s value. To mitigate this effect, we introduce a normalization factor that accounts for the total decay-weighted influence capacity of the descendant set. This approach functions analogously to softmax normalization [12], ensuring that each descendant contributes in proportion to its relative significance rather than its absolute presence.

We define a normalization factor $Z(\sigma)$ as the sum of decay values across all valid descendants:

$$Z(\sigma) = \sum_{\sigma' \in C(\sigma)} \mathbb{I}[d(\sigma, \sigma') \leq d_{\max}] \cdot f(d(\sigma, \sigma'))$$

Now, we modify the recursive feedback term to normalize each descendant’s contribution:

$$\beta(\kappa) = 1 + \sum_{\sigma' \in C(\sigma)} \mathbb{I}[d(\sigma, \sigma') \leq d_{\max}] \cdot \frac{f(d(\sigma, \sigma')) \cdot S(\sigma')}{Z(\sigma)}$$

This prevents Bob’s signal from gaining undue strength simply by mentoring many people, and instead rewards those interactions that lead to meaningful results, like Charlie’s project.

6.6 Amplification Cap

Even with the application of a depth threshold and normalization, a signal may still accrue excessive strength if it resides at the origin of a particularly impactful causal subtree. To mitigate the risk of unbounded amplification, we define a recursive amplification cap: a fixed upper bound on the extent to which the recursive modifier $\beta(\kappa)$ may enhance the base signal strength. This constraint ensures that signal valuations remain bounded, interpretable, and robust against disproportionate inflation, particularly in cases where low-effort or opportunistic actions are indirectly linked to high-value outcomes.

We implement this by enforcing a constraint on the final computed strength $S(\sigma)$:

$$S(\sigma) \leq \alpha(\theta_\sigma, t_\sigma) \cdot \gamma(a_\sigma) \cdot (1 + \epsilon) \tag{2}$$

Where:

- $\alpha(\theta_\sigma, t_\sigma)$: base signal strength
- $\gamma(a_\sigma)$: credibility modifier for the actor
- ϵ : tunable amplification limit (e.g., 1 for 2x cap)

Even if Charlie’s work is extremely influential, Alice’s signal won’t grow beyond the cap.

6.7 Attribution Weighting

Up until this point, each downstream signal $\sigma' \in C(\sigma)$ has been treated as being fully attributable to a single upstream signal σ . In practice, downstream contributions often emerge from the combined influence of multiple prior signals. For example, a founder may be mentored by several individuals, a team might form through a sequence of introductions, or a token launch could result from multiple collaborative efforts.

To avoid over-attribution and ensure fairness, we introduce a causal attribution weighting mechanism. This approach distributes the influence of a downstream signal proportionally across all relevant upstream signals, providing a more accurate reflection of shared causality.

We define a credit weight w_{ij} for the influence of upstream signal i on downstream signal j :

$$w_{ij} = \frac{1}{d_{ij}} \cdot \frac{1}{k_j}$$

Where:

- d_{ij} : the causal distance between upstream signal i and downstream signal j
- k_j : the total number of upstream contributors to j

This formulation gives more weight to closer causal ancestors (i.e. shorter paths = stronger influence) and spreads credit among all peer contributors, preventing inflation. Now we apply this weight to each term in the recursive sum, modifying the normalized recursive impact as:

$$\beta(\kappa) = 1 + \sum_{\sigma' \in C(\sigma)} \left[\mathbb{I}(d(\sigma, \sigma') \leq d_{\max}) \cdot w_{\sigma, \sigma'} \cdot \left(\frac{f(d(\sigma, \sigma')) \cdot S(\sigma')}{Z(\sigma)} \right) \right]$$

If Charlie's project was influenced by both Bob *and* Alice, recursive credit is split proportionally.

6.8 Full Signal Strength

Now that we've constructed the components of signal strength step by step, we can bring everything together into a single unified formula that defines the strength of a signal σ .

Let:

- $\alpha(\theta_\sigma, t_\sigma)$: Base signal strength from diminishing returns
- $\beta(\kappa_\sigma)$: Recursive impact modifier and attribution Weighting
- $\gamma(a_\sigma)$: Credibility modifier for the actor
- ϵ : Max amplification factor (e.g. $\epsilon = 1$ for a $2\times$ cap)

Then the uncapped signal strength is:

$$S^*(\sigma) = \alpha(\theta_\sigma, t_\sigma) \cdot \beta(\kappa_\sigma) \cdot \gamma(a_\sigma)$$

And the final capped signal strength is:

$$S(\sigma) = \min(S^*(\sigma), \alpha(\theta_\sigma, t_\sigma) \cdot \gamma(a_\sigma) \cdot (1 + \epsilon))$$

6.9 Total Actor Contribution

To compute the total signal strength for a participant a , we sum the strength of all signals they have emitted:

$$\Sigma(a) = \sum_{\sigma \in \Sigma_a} S(\sigma)$$

Charlie is credited for his direct actions. Bob gains recursive credit for mentorship. Alice accrues recognition for initiating the chain of participation.

7 Signal Analyzers and Lenses

To operationalize the computation of signal strength and support interpretability, the framework introduces the concept of a *Signal Analyzer*, a modular evaluation engine that takes signals as input, computes their strength according to the model described above, and outputs metrics to applications, dashboards, agents and other members of the network.

Each Signal Analyzer acts as a programmable interpretant: it applies a particular *lens* to the raw signal graph and renders it actionable for a given use case, such as reputation scoring, contribution tracking, airdrop planning, and so on.

7.1 Inputs and Outputs

The Signal Analyzer ingests a stream of signals, each as a tuple: $\sigma = (a, t, \theta, \kappa)$ and produces:

- $S(\sigma)$: Final signal strength for each signal
- $\Sigma(a)$: Cumulative signal strength for each actor
- $\Sigma(\theta)$: Aggregate strength per signal type

Optionally, analyzers can be paired with *Signal Filters* that scope analysis to specific domains (e.g. only economic signals, or only cultural signals), enabling specialized views and segmentation.

7.2 Graph-Based Processing Architecture

Signal strength is calculated through a combination of:

- Static metadata (signal type, timestamp, actor)
- Dynamic graph traversal (causal ancestry and descendant tracing)
- Recursive weighting (decay, attribution, normalization)
- Actor-level modifiers (credibility adjustments)

These components can be visualized as a directed acyclic graph (DAG) where:

- Nodes represent emitted signals
- Edges represent causal relationships
- Weight propagation flows backward from leaves to roots

7.3 High-Level Flow Diagram

To illustrate this architecture, we include a schematic overview of signal evaluation:

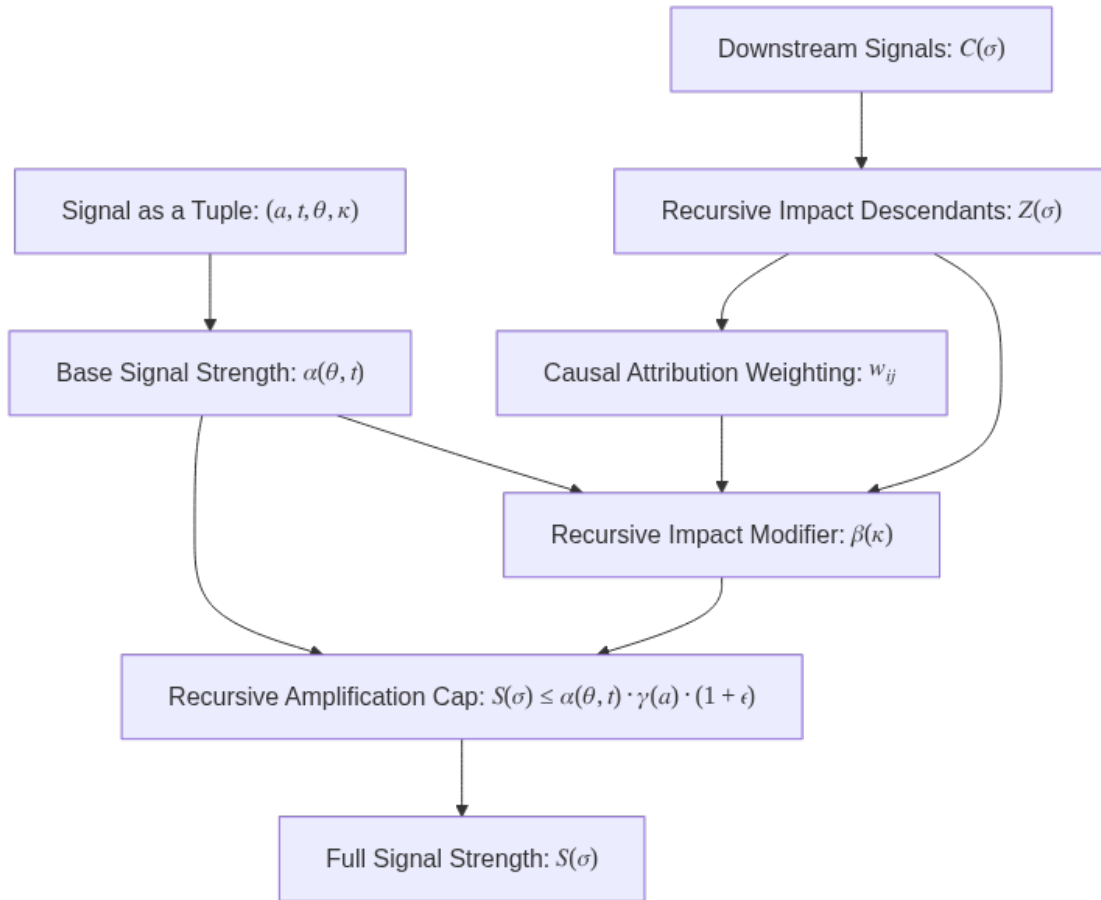


Figure 1: Schematic of a semiotic interpreter mechanism or lens.

This diagram captures the evaluation flow:

1. A signal is emitted and registered in the graph
2. Its base strength is computed from its type and history
3. Recursive contributions from downstream signals are traced and aggregated
4. The signal is clipped to enforce caps
5. Outputs are stored and made queryable via user dashboards or API endpoints

Each Signal Analyzer functions as a kind of *semiotic agent*, interpreting the network in a way that balances precision with symbolic flexibility. Multiple analyzers can coexist, some optimized for airdrop qualification, others for cultural alignment, reputation curation, or coordination intelligence.

This design supports pluralistic governance and adaptive evaluation. As the network evolves, new analyzers may emerge organically, reflecting the needs and interpretive frames of distinct communities and actors.

8 Evolving Trust Model and Emergent Interpretation

As the network matures and the signal graph increases in density, the need arises for more sophisticated interpretations of trust, reputation, and social alignment. While raw signal strength captures participation and impact, it does not by itself account for the subjective experiences of individual participants.

To address this, we introduce a secondary interpretive layer grounded in the concept of *emergent trust*. This layer builds on agreements and relationships formed in the network, leveraging participant feedback to construct a dynamic trust graph. Its goal is to move beyond absolute signal strength toward contextually grounded, relational credibility.

8.1 EigenTrust-Based Aggregation

To aggregate local trust values into global reputations, we draw from the EigenTrust algorithm [13], which computes transitive trust in a peer-to-peer network using iterative matrix propagation.

Let s_{ij} be the net trust that participant i assigns to participant j , based on past outcomes:

$$s_{ij} = \text{sat}(i, j) - \text{unsat}(i, j) \quad (3)$$

To normalize these values into a local trust vector c_{ij} that forms a probability distribution:

$$c_{ij} = \frac{\max(s_{ij}, 0)}{\sum_k \max(s_{ik}, 0)} \quad (4)$$

Then, using an iterative approach, we compute the global trust vector t as:

$$t^{(k+1)} = \alpha \cdot C^\top t^{(k)} + (1 - \alpha) \cdot e \quad (5)$$

Here, $\alpha \in [0, 1]$ is a damping factor, and e is an initialization vector (essentially a set of trusted participants in the network). The resulting vector t captures transitive trust, enabling reputational inference even in the absence of direct interaction. For instance, Bob’s credibility may increase not only through Charlie’s endorsement but also through Bob’s indirect connection to other trusted actors.

8.2 Integration with the Signal Strength Model

The global trust vector is formally integrated into the core valuation model through the actor credibility modifier $\gamma(a)$, as introduced in subsection 6.6. For convenience, the final signal strength of a given signal σ is described again in this section as:

$$S(\sigma) = \min(S^*(\sigma), \alpha(\theta_\sigma, t_\sigma) \cdot \gamma(a_\sigma) \cdot (1 + \epsilon))$$

Here, $\gamma(a_\sigma)$ is computed via one or more trust vectors associated with relevant interpretant lenses. This formulation ensures that impactful contributions from low-trust actors are discounted, while sustained, contextually valued behavior is amplified.

8.3 Trust as Interpretant: Modular Lenses

A core refrain of the exposition of the signals framework in this paper is the semiotic nature of signals. To re-iterate: trust is not treated as a single monolithic or objective scalar, but as a semiotic *interpretant*, as a modular *lens* through which actor behavior is contextualized and assessed. Thus, various different evaluative mechanisms may apply distinct trust lenses, which could include:

- An *economic lens* to determine eligibility for an airdrop based on actors' alignment signals
- A *cultural lens* that focuses on cultural fluency, participation, or memetic creativity
- A *governance lens* for governance mechanisms like connection-oriented cluster matching [14]

These lenses may coexist and operate independently, supporting pluralistic notions of legitimacy and enabling trust to vary across evaluative contexts. Under this model, credibility is not an inherent trait but an evolving signal contingent on perspective and domain.

This pluralism ensures that the network does not converge prematurely on a singular reputation metric. Instead, trust is understood as emergent, contextual, and subject to being contested, interpreted through lenses that evolve with the values and needs of the network.

9 Signal Taxonomy

While the Signals Framework supports the emergence of new and unstructured signal types, it is also useful to provide a foundational taxonomy for analysis, coordination, and interface design. This taxonomy organizes signal types by domain, effort level, impact scope, and repetition pattern.

Each signal type is treated as a semiotic object, defined not only by the action it encodes, but by its interpretive attributes. These attributes are used by Signal Analyzers and dashboards to classify, filter, and weight signals in context.

9.1 Core Attributes

The core classification dimensions are:

- **Domain:** The social, productive, or symbolic context in which the signal operates.
- **Effort:** An estimate of the action's difficulty or resource intensity (Low / Medium / High).
- **Impact:** The signal's scope of influence (Local / Network-wide / Recursive).
- **Repetition:** Whether the signal is one-time, episodic, or continuous.

9.2 Example Signal Types

Signal Type	Domain(s)	Effort	Impact	Repetition
Referral	Relational	Low	Recursive	Episodic
Introduction	Relational	Low	Local	Continuous
Connection	Relational	Low	Local	Continuous
Mentorship	Governance, Relational	High	Recursive	Episodic
Skill Contribution	Productive	High	Network	Episodic
Join Team	Productive, Relational	Medium	Recursive	One-time
Register Project	Governance, Productive	High	Recursive	One-time
Launch Token	Economic, Productive	High	Recursive	One-time
User Research Participation	Governance	Medium	Local	Episodic
Publish Network Content	Creative, Cultural	Medium	Network	Episodic
Publish Project Content	Creative, Productive	Medium	Local	Episodic
Host Event	Cultural, Relational	High	Network	Episodic
Join Event	Cultural	Low	Local	Continuous
Purchase Token	Economic	Medium	Recursive	Episodic
Hold Token (90d+)	Economic	Low	Recursive	Continuous

Table 1: Example signal types and their interpretive attributes

10 Conclusion

The Signals Framework proposes a new foundation for sense-making, coordination, and recognition in decentralized networks. By treating contributions not as fixed transactions but as contextual, semiotic signals, the framework supports a richer grammar of participation, one that values not only what is done, but how it resonates, propagates, and aligns with the network’s intrinsic values system.

This approach moves from prescriptive incentives to interpretive meaning, from centralized scores to distributed trust, reflecting a shift in how digitally native communities may coordinate, not by trying to quantify every single action, but by listening to their own semiotic feedback loops.

The model is designed to scale with the network insofar as it can begin with lightweight event tracking and gradually incorporate richer feedback loops. This modularity allows communities to define their own evaluative lenses, in ways that work best for their specific needs.

There are of course several areas for future work, including agent-based simulation and modeling, and scenario modeling for airdrops. For instance, earlier research proposed applying agent-based complexity science to public blockchain design in order to capture emergent trust dynamics [15], which is very relevant to this framework. There are also areas that need further consideration around sybil resistance, and what the trade-off space is in this regard.

Another area that deserves particular scrutiny and critique is with regards to the risk of emergent panopticism. We have yet to fully understand how to mitigate the risk of inadvertently creating systems such social-credit scores or mass surveillance apparatus. Future work should focus on the integration of Privacy Enhancing Technologies (PETs) and elective obfuscation of signals.

Overall, the Signal Framework represents an effort to acknowledge the complexity of human interaction and to honor the true value that emerges from human relationships. In an age of exponential technological innovation and relentless abstraction, authentic human relationships will become the most valuable artefacts in the world.

Appendix A Formal Properties of the Signal Model

Proposition: Signal Strength is Bounded

Proposition. For any signal σ , the final signal strength $S(\sigma)$ is bounded above by:

$$\alpha(\theta_\sigma, t_\sigma) \cdot \gamma(a_\sigma) \cdot (1 + \epsilon)$$

Proof. Let $S^*(\sigma) = \alpha(\theta_\sigma, t_\sigma) \cdot \gamma(a_\sigma) \cdot \beta(\kappa_\sigma)$ denote the raw (uncapped) signal strength. By the recursive cap mechanism defined in Equation 2, the final signal strength is:

$$S(\sigma) = \min(S^*(\sigma), \alpha(\theta_\sigma, t_\sigma) \cdot \gamma(a_\sigma) \cdot (1 + \epsilon))$$

By definition of the min function, $S(\sigma)$ is always less than or equal to the cap term:

$$S(\sigma) \leq \alpha(\theta_\sigma, t_\sigma) \cdot \gamma(a_\sigma) \cdot (1 + \epsilon)$$

Therefore, the signal strength is upper-bounded by a multiple of its base value and actor credibility. ■

Lemma: Convergence of Recursive Impact Modifier

Lemma. Let $\beta(\kappa)$ be the recursive impact modifier for a signal σ , defined as:

$$\beta(\kappa) = 1 + \sum_{\sigma' \in C(\sigma)} I[d(\sigma, \sigma') \leq d_{\max}] \cdot \frac{f(d(\sigma, \sigma')) \cdot S(\sigma')}{Z(\sigma)}$$

Assume:

- The causal graph is a finite directed acyclic graph (DAG).
- The decay function is geometric: $f(d) = \lambda^d$, with $0 < \lambda < 1$.
- The recursive depth is bounded: $d(\sigma, \sigma') \leq d_{\max}$ for all $\sigma' \in C(\sigma)$.
- Signal strengths $S(\sigma')$ are non-negative and finite.

Proof. Let $C_d(\sigma)$ denote the set of causal descendants of σ at depth d . Then we can write:

$$\beta(\kappa) = 1 + \frac{1}{Z(\sigma)} \sum_{d=1}^{d_{\max}} \sum_{\sigma' \in C_d(\sigma)} \lambda^d \cdot S(\sigma')$$

Since:

- λ^d decays exponentially with d ,
- $C_d(\sigma)$ is finite for each depth d , and
- $S(\sigma')$ is finite and non-negative for all σ' ,

then the double sum is finite. Furthermore, the normalization factor $Z(\sigma) = \sum_{\sigma' \in C(\sigma)} \lambda^{d(\sigma, \sigma')}$ is positive and finite under the same constraints.

Hence, $\beta(\kappa)$ is a convergent expression and yields a finite, well-defined output. ■

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