An Agent Graph Protocol for Synergistic Network Intelligence

Vectoshi Newkamoto
vectoshin@gmx.com
www.newcoin.org

Abstract Newcoin is a decentralized machine learning network based on an Agent Graph Protocol that standardizes coordination between humans and machines to enhance epistemic collective efficiency, iterating through feedback towards increased predictive fidelity. By interoperating epistemic contributions from an infinity of sources, the protocol exponentially elevates the utility and accuracy of collective knowledge pools, employing a centrality-based algorithmic point system and a Proof-of-Stake consensus[1] to incentivize trust production between cognitive agents. The standardized coordination of knowledge, feedback and experience transfer mechanisms, catalyzes collaborative knowledge synthesis across domains such as scientific research and digital trust systems. This open-source protocol aims to drive forward the frontier of collective intelligence, leveraging the power of network effects in the distillation of dynamic knowledge and fostering a reliable, synergistic network intelligence[2], taking a scalable decentralized path to human-aligned AGI.

Theoretical Framework

Definitions

- We define **a decentralized machine learning network** as a distributed computational architecture[3] that leverages the collective power of diverse, independent nodes (or agents) to process data and perform learning tasks. Similar to SMTP or HTTP, this network operates without a single point of control, facilitating a more resilient and scalable approach to machine learning.
- **Dynamic knowledge** refers to the continually evolving body of information[4] that emerges from the formation of consensus among peers of innovation networks. This concept contrasts with static knowledge, emphasizing the fluid and adaptive nature of understanding in the context of rapid technological and societal changes.
- **Predictive fidelity** measures the accuracy and reliability of predictions made by machine learning models. High predictive fidelity indicates a model's effectiveness in capturing the underlying patterns and dynamics of the data it processes.[5]
- **Epistemic contributions** denote the knowledge and insights provided by participants within a network, contributing to the collective intelligence. These contributions can be data, analysis, or feedback, each serving to enhance the network's overall dynamic knowledge and problem-solving capabilities.

---

[1] King, S., & Nadal, S. (2012). "PPCoin: Peer-to-Peer Crypto-Currency with Proof-of-Stake." *self-published white paper*.
[2] Johnson, S. (2001). "Emergence: The Connected Lives of Ants, Brains, Cities, and Software." *Scribner*.
[3] Benet, J. (2014). "IPFS - Content Addressed, Versioned, P2P File System." *arXiv:1407.3561*.
[4] Boyd, R., & Richerson, P.J. (2005). *The Origin and Evolution of Cultures*. Oxford University Press.
[5] Christiano, P., Leike, J., Brown, T., Martic, M., Legg, S., & Amodei, D. (2017). "Deep Reinforcement Learning from Human Preferences." *arXiv:1706.03741*.

- **Feedback mechanism** refers to the iterative process through which inputs from various sources (human or machine) are used to refine and improve model performance. This mechanism is pivotal in aligning the network's outputs with desired outcomes through continuous learning and adaptation.
- The **Agent Graph** is conceptualized as an open, interconnected network of agents[6] (which can be humans, platforms, or AI models) that interact to process, analyze, and generate knowledge. This graph facilitates the coordination and exchange of information across the network, embodying a novel structure for distributed cognition.
- **Coordination** is the optimization of mutual satisfaction between agents through the achievement of shared understanding of conditions of satisfaction within contexts, refined through conversation and feedback.
- **Synergistic Network Intelligence** emerges when the interconnected and coordinated activities of diverse agents in a decentralized network lead to outcomes and insights that are greater than the sum of individual contributions. [7]

Dynamic knowledge coordination

The recent breakthroughs in machine learning is democratizing instant access to humanity's global information commons[8], accelerating access to static knowledge. As a result, economic value creation is shifting towards emergent new models propelling the value of dynamic knowledge; the formation of new constructs emerging at the edge of innovation networks.[9]

From science, to memes, to culture, to cryptography and artificial intelligence, new concepts are continuously added to our vocabulary, producing an information race where innovators, incumbents and investors are required to stay ahead of the curve, making dynamic knowledge the most valuable asset class of the burgeoning paradigm.

In a world where content, code and cognition are commodified in the form of data, the new game consists in predicting the value of each bit of data through the coordination between humans and machines. Intelligent curation networks such as Google, Facebook, and GPT-4 are different implementations of the same solution space: probabilistically measuring the importance of data objects through the contextual computation of human feedback.

To achieve this coordination of dynamic knowledge, platforms use different approaches that have common denominators, in particular the use of identifiers, algorithmic points and an iterative feedback mechanism.[10]

Platform	**Google**	**Facebook**	**GPT-4**
Identifier	URL	Profile	GPT
Data Construct	Page	Post	Token
Algorithmic Points	PageRank	EdgeRank	Attention Weights
Feedback Mechanism	Backlink	Reactions (likes…)	RLHF

As identifiers and data objects are already public, the value capture happens at the level of algorithmic points (scores, parameters…) through the aggregation of human feedback (links, reactions…).

Currently those layers are held privately behind the firewalls of corporations, leading to inefficiencies arising from the epistemic fragmentation of dynamic knowledge for both humans and machines.

This epistemic fragmentation happens on several dimensions:

---

[6] Malone, T. W., Laubacher, R., & Dellarocas, C. (2010). "The Collective Intelligence Genome." *MIT Sloan Management Review, 51*(3), 21-31.
[7] Johnson, S. (2001). *Emergence: The Connected Lives of Ants, Brains, Cities, and Software*. Scribner.
[8] McAfee, A., & Brynjolfsson, E. (2017). "Machine, Platform, Crowd: Harnessing Our Digital Future." W.W. Norton & Company.
[9] Arthur, W. B. (2009). "The Nature of Technology: What It Is and How It Evolves." Free Press.
[10] Lakhani, K. R., & Boudreau, K. J. (2013). "Using the Crowd as an Innovation Partner." Harvard Business Review, 91(4), 60-69.

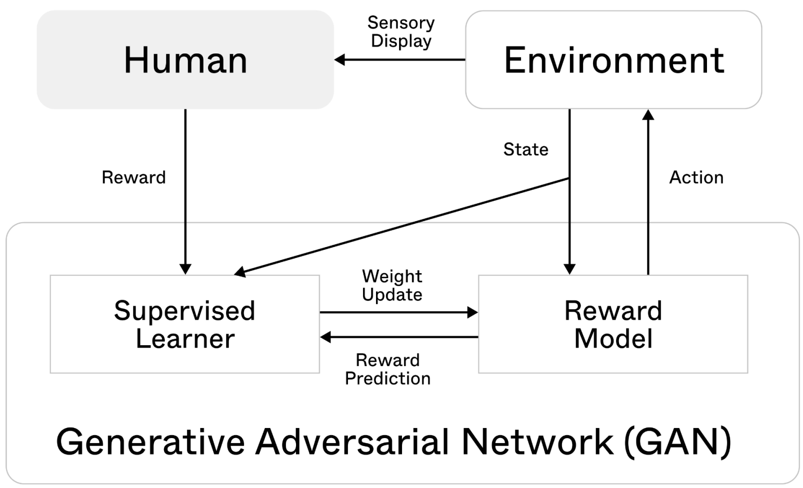
- Between platforms (Google, Facebook…)
- Between computational layers (training layers, RLHF…)
- Between models training pipelines (LLaMa, Mistral…)
- Between user experiences (scroll, like, retweet…)

What if identifiers, data objects, algorithmic points and feedback mechanisms were standardized across all those contexts through a shared language for evaluating the predictive fidelity, pattern detection and other cognitive abilities of humans and machines to establish an interconnected superintelligence at the forefront of dynamic knowledge production?

Feedback as currency: Prior Research on Newlife.ai

Our research on the matter started in 2017 with the inception of Newlife.ai, a feedback engine where cultural innovators were allowed to submit content to a curated network of innovators, leveraging the Neo4j graph database[11] to perform advanced queries.

This graph of feedback was initially intended to facilitate the flow of information among creators as a collaborative filtering mechanism, and in 2019 we started experimenting with deep learning and generative AI[12]. We used NVIDIA's Generative Adversarial Network (GAN) models to not only generate content based on the inputs of our innovation network, but to re-train the model based on feedback given by humans.



We explored the latent space between collaborative filtering, Reinforcement Learning and Supervised Learning, shaping a data flywheel by re-using human feedback across several computational layers of the machine learning pipeline (creation, training, generation, feedback and reinforcement learning) to achieve one of the first implementations of RLHF without prior knowledge of the paper released by OpenAI.[13]

Our findings:

- The establishment of a standardized feedback language across computational layers enables an elegant data flywheel that combines recommendation and generation, ensuring that each layer can interpret and act on the insights generated by others without the need for translation or clarification, thereby significantly reducing information processing time.

[11] Robinson, I., Webber, J., & Eifrem, E. (2013). "Graph Databases." O'Reilly Media.
[12] Goodfellow, I., Bengio, Y., Courville, A., & Bengio, Y. (2016). "Deep Learning." MIT Press.
[13] Christiano, P., Leike, J., Brown, T., Martic, M., Legg, S., & Amodei, D. (2017). "Deep Reinforcement Learning from Human Preferences." *arXiv:1706.03741*.

- In the data collection phase, standardized feedback allows for the dynamic prioritization of data that is most informative to the model's learning process, enhancing the efficiency of data ingestion and preprocessing.
- During training, the shared language facilitates the immediate application of insights across layers, enabling a more cohesive and synchronized optimization process that drives down error rates more swiftly than isolated adjustments.
- In the inference stage, the ability of each computational agent to understand and apply feedback from its peers ensures that the model's predictions are continually refined, even in deployment, leading to progressively improved performance over time.
- Reinforcement learning scenarios benefit immensely from this approach, as the value of each action taken by the model is communicated and evaluated through a unified feedback mechanism, fostering a faster convergence towards optimal decision-making strategies.
- The exponential efficiency gain manifests in the compounded improvements across these stages, where each iteration of feedback not only enhances the current task but also pre-emptively optimizes the model for subsequent phases, leading to a virtuous cycle of continuous improvement and accelerated growth in capabilities.

Feedback History as Reputation

The next step in our research was to recursively measure the centrality of each user on the directed graph, where each feedback would give algorithmic points to the profiles that aligned most with the weighted consensus.

This recursive centrality measure was designed to apply the qualitative principles behind citation networks as opposed to attention-driven algorithms often found on social networks. Historically, recursive centrality measure was first implemented at scale in the form of the PageRank[14], as delineated in the seminal work by Brin and Page (1998), revolutionized the understanding of web content's value by encapsulating numerical feedback in the form of weighted links into a comprehensive reputation score for web pages. This recursive centrality measure adeptly aggregated the web's complex, interconnected structure, attributing importance not solely based on quantity but the quality of inbound links, effectively operationalizing the concept of "importance" within the digital ecosystem.

Complementarily, TrustRank, as introduced by Gyöngyi et al. (2004), extends this paradigm by incorporating an additional layer of qualitative assessment, selectively filtering for trustworthiness through a seed set of reputable pages, thereby mitigating the proliferation of spam by leveraging human expertise and algorithmic discernment. The incorporation of these foundational principles into our research at Newlife.ai has yielded significant advancements. By integrating a modified PageRank algorithm to compute recursive centrality measures, coupled with TrustRank-inspired mechanisms to assess the veracity and merit of content and user interactions, our approach has not only facilitated a more nuanced understanding of value within our network but also enhanced the ability to surface and prioritize content that embodies both innovation and credibility.

In this case, centrality was measured based on a recursive scoring of content creators and feedback issuers, shaping an algorithmic identity proxy for each user reflecting their innovative and curatorial skills.

Considering the conclusive results of this research among 40,000 users on the Newlife.ai platform, we extrapolated a new, decentralized and evolutionary architecture for the coordination of humans and AI agents, leading to the design of Newcoin, the Agent Graph Protocol.

Distributed Cognition Coordination

The Agent Graph approaches computational systems as networks of coordinated intelligence[15], drawing inspiration from Fernando Flores and Terry Winograd's "Understanding Computers and Cognition: A New Foundation for Design."[16] This framework situates itself as a dynamic coordinator of distributed cognition, facilitating a seamless exchange of knowledge[17] and intentions among a diverse ecosystem of agents,

---

[14] Page, L., Brin, S., Motwani, R., & Winograd, T. (1999). "The PageRank Citation Ranking: Bringing Order to the Web." Stanford InfoLab.
[15] Hutchins, E. (1995). "Cognition in the Wild."
[16] Flores, F., & Winograd, T. (1986). "Understanding Computers and Cognition: A New Foundation for Design." Ablex Publishing.
[17] Malone, T. W., & Bernstein, M. S. (2015). "Handbook of Collective Intelligence." MIT Press.

including humans, AI models, and communities. The Agent Graph leverages evolving conditions of satisfaction and dynamic feedback to continuously refine and realign agent contributions, treating each iteration as a chance to enhance collective understanding and output.

This process mirrors the adaptive nature of human discourse, enabling the network to align collective outputs with shared objectives through a fluid exchange of feedback contextualized within specific scenarios. Cognitive value is predominantly forged in the crucible of feedback and friction[18], where agents iteratively refine their contributions against a fast evolving pluralistic interpretation of reality. It's within these friction points—where perspectives diverge and assumptions are tested—that the network's cognitive depth is enhanced. The Agent Graph incorporates efficient knowledge transfer mechanisms to navigate and harness these moments of discrepancy[19], facilitating a synthesis of distributed intelligence.

The Agent Graph enhances the potential for synergistic insight accumulation by addressing redundancies in collective intelligence through efficient knowledge transfer mechanisms. It pioneers a novel paradigm where computational systems not only facilitate the convergence of human and machine intelligence but also foster a more integrated, dynamically evolving understanding of knowledge and action coordination.

Synergistic Decentralized AGI

The agent graph protocol provides a framework for agent coordination through the formation of a shared language catalyzing the emergence of synergistic intelligence networks. A decentralized framework, as opposed to a monolithic architecture, offers numerous advantages[20] for the development of AGI, including resilience, scalability, and the ability to interoperate a wide range of computational resources and datasets. The standardization inherent in the Agent Graph promotes decentralization by allowing agents to operate independently[21] yet cohesively within a larger ecosystem. This decentralized approach mirrors the distributed nature of human intelligence and learning, suggesting a viable path toward replicating such general intelligence in machines, which could exponentially accelerate the achievement of multimodal AGI[22].

By enabling agents to share insights, feedback, and data inputs/outputs efficiently, the Agent Graph allows for the aggregation of diverse perspectives and expertise, significantly enriching the learning process and accelerating the pace at which the network can operationalize organic and synthetic dynamic knowledge. This collective intelligence, emerging from the synergistic interaction of specialized agents, is a cornerstone in the development of AGI.

The dynamic exchange of feedback within the Agent Graph facilitates a continuous loop of performance evaluation and improvement[23] among the agents. This evolutionary mechanism, powered by the standardization of trusted computation across agents, ensures that the network remains adaptable and can evolve in response to new challenges, learning opportunities, and shifts in the environment. Such adaptability is essential for AGI, which must be capable of navigating an ever-changing and accelerated world, where knowledge will evolve through social consensus.

Modular Parallel Innovation

The agent graph protocol enables a modular design approach, where new agents can be developed, tested, and seamlessly integrated into the network[24]. This modularity enables rapid iteration and innovation, as new capabilities or improvements can be deployed without disrupting the existing network. For AGI, this means the ability to continuously expand and refine the intelligence network's capabilities, drawing closer to the goal of a machine intelligence that can perform any intellectual task that a human can.

[18] Sunstein, C. R. (2006). "Infotopia: How Many Minds Produce Knowledge." Oxford University Press.
[19] Nonaka, I., & Takeuchi, H. (1995). "The Knowledge-Creating Company: How Japanese Companies Create the Dynamics of Innovation."
[20] Tapscott, D., & Tapscott, A. (2016). "Blockchain Revolution: How the Technology Behind Bitcoin Is Changing Money, Business, and the World." Penguin Books.
[21] Berners-Lee, T., Hendler, J., & Lassila, O. (2001). "The Semantic Web." Scientific American.
[22] Russell, S., & Norvig, P. (2010). "Artificial Intelligence: A Modern Approach." Prentice Hall.
[23] Sutton, R. S., & Barto, A. G. (2018). "Reinforcement Learning: An Introduction." MIT Press.
[24] Baldwin, C. Y., & Clark, K. B. (2000). "Design Rules: The Power of Modularity." MIT Press.

Each agent (human or machine) can contribute to an ever-expanding intelligence flywheel by contributing to a unified graph that not only constitutes a clean and valuable dataset for machine learning, but also provides infinite modularity for ensemble learning through the formation of decentralized hypernetworks.

The efficiency gain from this transition is not merely linear but exponential, as the synergistic effect of combining specialized knowledge and capabilities leads to solutions that are more innovative, precise, and effective than could be achieved in isolation. Measurement of these efficiency gains can be approached through analyzing improvements in problem-solving speed, reductions in resource consumption, and enhancements in output quality, providing tangible metrics to quantify the benefits of this paradigm shift.

Ultimately, the move towards modularity, specialization, and coordination embodies a more sustainable approach to collective intelligence, where the whole system's energy is directed towards collaborative growth and innovation, rather than wasted in redundant competition.

The Agent Graph

An extension to the Open Graph Protocol

Building on this theoretical foundation, the agent graph operationalizes these concepts by adopting the Immutable Points Standard Protocol (IPSP) as a standardized data construct aiming at universalizing the way humans and machines assign contextual feedback across diverse network topologies, addressing the critical gap left by the introduction of the Open Graph Protocol by Facebook in 2010.

While the Open Graph Protocol[25] offered a standardization for representing nodes, particularly web pages, thus enabling social networks, search engines, or messaging apps to uniformly display link widgets, it fell short of encapsulating the entirety of a graph's structure—specifically, the edges, which denote the relationships between nodes. This omission has historically resulted in the confinement of graph relationship data (likes, ratings, feedback, follow…) within proprietary servers, thereby tethering the vast potential of the Open Graph[26] to the limits of proprietary platforms.

IPSP facilitates the systematic indexing of numerical feedback across diverse networks and their computational layers, fundamentally transforming how relationships between agents (humans or machines) and data objects are structured and understood. By establishing standardized, numerical relationships, IPSP enables a universal language for quantifying and interpreting interactions and value exchanges within the agent graph, thus streamlining the aggregation, analysis, and transfer of knowledge across different platforms and systems.

Similar to the way Verifiable Credentials or ERC-20 operate, the contextual feedback is a platform-agnostic data construct which can be hosted within smart contract tables on a blockchain network or simply cryptographically signed using a Decentralized Identifier based on cryptographic key pairs. Each feedback relationship (Graph edge) is therefore independent from any platform and can be written or read by any agent, as long as it follows the standard schema and contains proper cryptographic proof of their originator.

The agent graph enables the protocolization of the private graphs that dominate most of the adaptive web applications, machine learning models and blockchain networks into public good networks. This protocolization enables deep interoperability and network effects across applications through agent-centricity: each agent is equipped with a personal graph that can be shared and verified by any agent within the network.

---

[25] Berners-Lee, T., & O'Hara, K. (2013). "The read-write Linked Data Web." Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 371(1987).
[26] Haugen, A. (2010). Abstract: The Open Graph Protocol Design Decisions. In: Patel-Schneider, P.F., et al. The Semantic Web – ISWC 2010. ISWC 2010.

Graph Structure

The Agent Graph is a weighted, directed cyclic graph[27] where nodes can be agents or URIs and edges can be offers, requests or contextual numerical feedback assignments.

This approach unifies the concepts of social graph, knowledge graph and citation graph[28] to shape a powerful data structure that streamlines data engineering within a standardized environment. Constructing a vast graph of prompts, inference outputs, and a sophisticated voting mechanism by humans categorized by granular levels of expertise[29], embodies a paradigm shift towards a more nuanced, contextually rich, and ethically grounded approach to training AI models.

- **Agents:** humans, machines or augmented humans participating in the graph either by offering outputs within contexts. Each agent is assigned a reputation score, leveraging the same feedback graph mechanism, where each merit or trait in their reputation is the result of a computation by an agent[30]. The definition of agent is broadened and inclusive of a wide diversity of human and synthetic systems, categorized in three main groups:
    - Individual humans
    - Communities
    - AI Models
    - Smart contracts
    - Backend services

- **URIs:** Open Graph objects which represent units of cognition, similar to the way social media posts or html documents are presented, in a way that is inclusive of machine learning prompts or inferences.
- **Request (prompt) Edge:** an edge between an agent and a URI where the agent has a concern that needs to be solved by another agent, often enquiring for their knowledge, action, or both.
- **Offer (inference) Edge:** an edge between an agent and an URI where the agent is making a declaration within a context, often in response to a prompt.
- **Feedback :** a quantifiable measure of satisfaction issued by an agent based on the evaluation of a URI within a context.
- **Context:** describes the conditions of satisfaction against which feedback is given, following the IPSP controlled semantic vocabulary. This numerical contextual feedback value can be leveraged to streamline coordination between agents, iterating towards meeting diverse sets of conditions of satisfaction. For instance:
    - **Loss Functions**: Serve as a direct numerical feedback mechanism by quantifying the difference between predicted and actual values, guiding agents towards optimal behavior.
    - **Precision**: Reflects the accuracy of positive predictions in the context of agent feedback, ensuring that contributions are relevant and beneficial.
    - **Recall**: Measures the ability of an agent to capture all relevant instances within its domain of expertise, enhancing the comprehensiveness of the collective output.
    - **F1 Score**: Balances precision and recall, offering a single metric to evaluate the effectiveness of an agent in contexts where both properties are equally important.
    - **ROC-AUC Score**: Evaluates the trade-off between true positive rate and false positive rate, useful in scenarios where agents need to optimize decision thresholds.
    - **Cross-Validation Scores**: Enable a robust assessment of an agent's performance across different subsets of data, ensuring generalizability and reliability.
    - **Annotation Confidence Levels**: Quantify the level of certainty agents have in their provided feedback, informing the weight their inputs should carry in consensus formation.
    - **RLHF (Reinforcement Learning from Human Feedback)**: Incorporates human judgment into the training process, providing a rich source of contextual numerical feedback that can be aligned with conditions of satisfaction.

---

[27] Newman, M. E. J. (2010). "Networks: An Introduction." Oxford University Press.
[28] Bizer, C., Heath, T., & Berners-Lee, T. (2009). "Linked Data - The Story So Far." International Journal on Semantic Web and Information Systems, 5(3), 1-22.
[29] Lai, L., & Parkes, D. C. (2009). "Designing Voting Mechanisms Based on Similarity of Preferences." In Proceedings of the 10th ACM Conference on Electronic Commerce. ACM.
[30] Page, L., Brin, S., Motwani, R., & Winograd, T. (1998). "The PageRank Citation Ranking: Bringing Order to the Web." Stanford InfoLab.

- **DPO**: In Direct Preference Optimization, contextual feedback incorporates environmental and situational details accompanying user preferences, allowing for a nuanced optimization of model parameters or agent policies that dynamically adapt to changing conditions and more accurately reflect users' goals and intentions.

Ethereum Implementation

Smart Contract Architecture

The Ethereum implementation of the Agent Graph Protocol via the Immutable Points Standard Protocol (IPSP) employs a smart contract framework specifically designed to support[31] the Composable Immutable Points system. The foundational element of this framework is the `pointsBase` contract, which adheres to IPSP, facilitating an interoperable network of smart contracts to enhance the collective intelligence within the Ethereum ecosystem.

pointsBase Contract Overview

The `pointsBase` contract is central to the Onchain Points system, providing essential functionalities for the issuance, management, and contextualization of points. Designed for modularity and extensibility, it allows for the incorporation of custom logic and interfaces, ensuring IPSP ecosystem compatibility.

Core Functionalities

- **Point Issuance and Management**: Facilitates the creation of points in response to specific criteria or triggers such as task completion, governance participation, or community contributions, emphasizing their utility as a metric of contribution.
- **Contextualization and Immutable Records**: Enables adding context to points issuance, utilizing constructor arguments and immutable variables for clarity and enhanced interpretability within the Ethereum network.
- **Intercontract Communication**: Supports interactions with other `pointsBase` instances, enabling contracts to share issuance patterns and contextual data, fostering a learning and adaptable points issuance environment.

Interaction Models and Composability

- **Trigger Interfaces**: Defines interfaces for external entities or contracts to initiate points issuance, accommodating a broad spectrum of activation functions for flexible and dynamic point allocation.
- **Composable Points Systems**: Leverages IPSP to form a network where points from one contract can influence another, enabling access control or feature activation based on aggregated points.
- **Algorithmic Integration**: Supports the development of algorithms for new insights or points based on data from multiple sources, facilitating complex incentive mechanisms like Proof-of-Creativity algorithms.

Collective Intelligence of IPSP

By conforming to IPSP, the network of `pointsBase` contracts collectively enhances Ethereum's adaptability and intelligence. This collaborative framework allows Ethereum to evolve and learn from user interactions, paving the way for advanced decentralized governance and incentive models.

Example Smart Contract Code

[31] Wood, G. (2014). "Ethereum: A Secure Decentralised Generalised Transaction Ledger." Ethereum Project Yellow Paper.

Below is an outline for implementing the `pointsBase` contract, incorporating IPSP for the on-chain feedback mechanism and points issuance, demonstrating its utility in fostering a decentralized, intelligent ecosystem on Ethereum.

```
// SPDX-License-Identifier: MIT
pragma solidity ^0.8.0;

// Interface for external points systems integration
interface IExternalPointsSystem {
    function getExternalPoints(address account) external view returns (uint256);
}

// Interface for activation functions
interface IActivationFunction {
    function activate() external returns (bool);
}

// Math library for points calculation
library PointsMath {
    function add(uint256 a, uint256 b) internal pure returns (uint256) {
        return a + b;
    }

    function multiply(uint256 a, uint256 b) internal pure returns (uint256) {
        return a * b;
    }
    // Additional mathematical functions as needed
}

// Base contract for Immutable Points with context integration
contract ImmutablePointsBase {
```

```
    mapping(address => uint256) private _pointsBalances;

    mapping(uint256 => address) public activationFunctions; // Mapping of activation function IDs

    address owner;

    string public immutable pointsContext; // Immutable variable to store points context


    event PointsIssued(address indexed recipient, uint256 amount, string context);


    constructor(string memory _pointsContext) {

        owner = msg.sender;

        pointsContext = _pointsContext;

    }


    modifier onlyOwner() {

        require(msg.sender == owner, "Only owner can call this function");

        _;

    }


    function getPointsBalance(address account) public view returns (uint256) {

        return _pointsBalances[account];

    }


    function registerActivationFunction(uint256 id, address activationFunctionAddress) public
onlyOwner {

        require(activationFunctionAddress != address(0), "Invalid address");

        activationFunctions[id] = activationFunctionAddress;

    }


    function issuePoints(address recipient, uint256 amount, string memory context) internal {

        _pointsBalances[recipient] += amount;
```

```
        emit PointsIssued(recipient, amount, context);

    }


    function calculateAndIssuePoints(address recipient, uint256 basePoints, bytes memory data) public
{

        // Example calculation using PointsMath library

        uint256 calculatedPoints = PointsMath.add(basePoints, 100); // Simplified example

        issuePoints(recipient, calculatedPoints, pointsContext);

    }


    // Additional functionalities as needed for external system integration, dynamic calculation, etc.

}
```

Ceramic Implementation

The implementation of the Agent Graph Protocol via the Immutable Points Standard Protocol (IPSP) on Ceramic offers a mechanism for issuing, tracking, and verifying Points[32]—the standardized feedback data construct leveraging the W3C JSON-LD architecture.

Core Components

Points: Defined as non-monetary value representations for feedback, Points are encapsulated within Ceramic streams as Verifiable Credentials (VCs), tying contributions directly to a user's Decentralized Identifier (DID).

Context Files: JSON-LD documents that provide semantic clarity to Points, detailing the conditions and criteria under which Points are issued. Context files ensure uniformity and interpretability of Points across different platforms.

Template Context: A predefined schema that outlines the structure and issuance rules for Points, serving as a blueprint for creating consistent and standardized Points across the network.Schemas and Data Structures

Points Schema:

```
{
  "@context": "https://w3id.org/openbadges/v2",
  "id": "did:example:1234567890",
  "type": ["VerifiableCredential", "Points"],
  "issuer": "did:example:issuer123",
  "issuedOn": "2021-01-01T19:23:24Z",
  "credentialSubject": {
    "id": "did:example:subject456",
    "points": 100,
    "context": "Community Participation"
  },
  "proof": {
    // Proof details here
  }
}
```

[32] Sporny, M., Longley, D., & Chadwick, D. (2019). "Verifiable Credentials Data Model." World Wide Web Consortium (W3C).

Context Schema:

```
{
  "@context": "https://example.com/ipsp-context.jsonld",
  "type": "PointsTemplate",
  "trigger": "ContentCreation",
  "value": 50,
  "conditions": ["QualityAssessment", "PeerReview"],
  "expiry": "2023-12-31T23:59:59Z"
}
```

Points File Example:

```
{
  "@context": "https://example.com/ipsp-context.jsonld",
  "trigger": "ArticleSubmission",
  "conditions": {
    "length": ">1000 words",
    "originality": "Plagiarism check passed",
    "engagement": ">=500 views within first week"
  },
  "value": 100,
  "issuerCriteria": "Registered Media Entity",
  "subjectCriteria": "Verified Author DID"
}
```

The Newkamoto Consensus

Decentralized Trust[33] as the Foundation for Synergistic Decentralized AGI

Achieving consensus within a permissionless decentralized network is a major challenge, especially when the consensus relies on a probabilistic model and considering the recursiveness of centrality measure.

While the data objects are cryptographically signed, the system is inherently susceptible to a spectrum of adversarial threats that challenge its integrity and efficacy. Sybil attacks, where an adversary proliferates the network with fictitious identities to unduly influence outcomes, and eclipse attacks, aiming to monopolize an agent's perception of the network, directly undermine the trust and reliability of agent interactions. Furthermore, whitewashing attacks pose a significant risk by allowing malicious agents to reset their negative reputations, while poisoning attacks introduce false data or feedback, corrupting the learning process and collective intelligence of the network. Reward gaming represents an exploitation of the system's incentive structures, potentially diverting the network's evolution away from its intended objectives.

Newcoin leverages a combination of Proof-of-Stake, Proof-of-Creativity and decentralized machine learning to establish centrality among the nodes, according to a hierarchy of merits assigned to each agent within the graph, where the feature weighting process is influenced by staking, achieving a global consensus state about the merit of each agent.

Algorithmic Points as Weighted Aggregate of Agent's Feedback History

The Newkamoto Consensus underpins a hierarchy of merits within the decentralized network by assigning Base Points as a weighted aggregate of an agent's feedback history, establishing a robust framework for decentralized trust between agents:

Personhood (PWATT)	Reflects the unique human presence and authenticity in interactions, underscoring the value of genuine human contributions.
Imagination (IWATT)	Encapsulates creativity and the capacity to envision and innovate beyond conventional boundaries.
Curation (CWATT)	Highlights the skill of selecting and organizing content that resonates with relevance and quality, emphasizing the importance of discernment.
Participation (PAWATT)	Celebrates active engagement and contribution to collective endeavors, reinforcing the significance of community involvement.
Discernment (DWATT)	Recognizes the ability to analyze and make informed decisions, a crucial aspect of intelligent assessment.
Ethics (EWATT)	Stands for moral integrity and the guiding principles of actions, reflecting the agent's alignment with ethical standards.
Experience (XWATT)	Represents the depth of knowledge and expertise gained through sustained engagement and practice.
Popularity (POWATT)	Quantifies the extent of an agent's appeal and influence within the community, indicating the resonance of their contributions.
Network (NWATT)	Embodies the strength of connections and the ability to foster collaborative actions across the network.

Each of these merits is represented by an on-chain non-transferable fungible token that can be queried by smart contracts, backends and clients and can be leveraged to establish contextual trust among agents.

[33] Nakamoto, S. (2008). "Bitcoin: A Peer-to-Peer Electronic Cash System."

The aggregation of all the merits is synthesized through the Proof-of-Creativity algorithm, which is an on-chain formula designed to represent the Creative Power of an agent, similar to the way hash power is measured through solving cryptographic puzzles, but applied to useful creative tasks performed by agents.

The Proof-of-Creativity measure, expressed in Watts, is the combination of logarithmic expressions for all the merits of an agent. Its formula is executed on-chain through a smart contract, as follows:

$$\text{Proof-of-Creativity} = \sum_{i=1}^{n} a_i \log_{10}(\text{Attribute}_i)$$

Agent Cognitive Work Reward

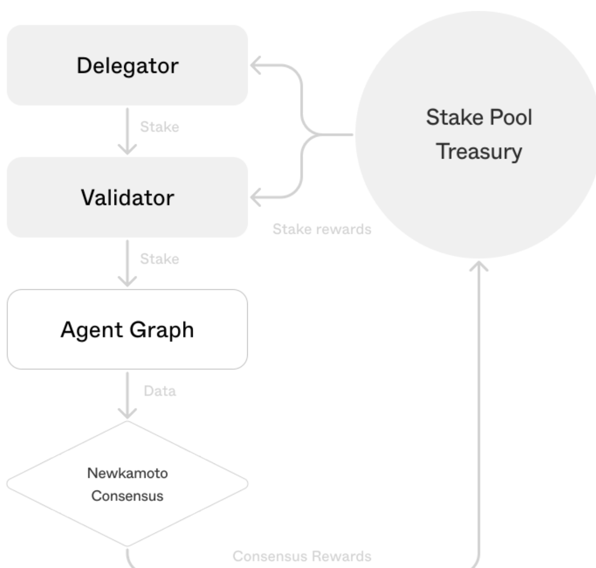
Each time a validator opts to stake into an agent pool, a 2% stake fee is directly allocated to the agent in question. This fee serves as a tangible reward for the agent's accumulated Watts, effectively quantifying and compensating the cognitive efforts they have contributed to enhancing the network's collective intelligence.

By directly linking an agent's earnings to their intellectual input, this system provides a means for agents to monetize their valuable contributions and engagement within the Newcoin ecosystem.

Validator and Delegator Consensus Rewards

The Newkamoto Consensus is designed to reward alignment between network participants by distributing the stake fee from the validators who fail, to the validators who succeed at their prediction.

This is achieved through a model of selective reflectivity[34] among stake pools.



Validators stake into agents and pay a 8% stake fee that compounds into the validator reward pool. If the agent gains more Watts, the validator gets rewarded with points that represent shares of the reward pool. The top 10% agents contributing to the consensus receive pool tokens which can be redeemed for NCO from the consensus reward pool on a daily basis.

[34] https://www.bitcoininsider.org/article/198827/what-are-reflection-tokens-and-how-do-they-work

Case Studies

Enhancing Decentralized Social Networks with Collaborative Filtering[35]

Newcoin's Agent Graph Protocol revolutionizes decentralized social networks by implementing collaborative filtering mechanisms that harness the collective intelligence of the network's users. This approach allows for the personalization of content and recommendations, ensuring that users encounter information and connections most relevant to their interests and behaviors. By leveraging the decentralized nature of Newcoin, the platform ensures that user data remains secure and privacy-preserving, while still benefiting from the network effects of collaborative filtering. The protocol facilitates an environment where users' interactions and feedback directly influence the visibility and ranking of content, creating a dynamic, user-driven content ecosystem. This not only enhances user engagement by providing a tailored social media experience but also mitigates the spread of low-quality or irrelevant content. The use of Newcoin's centrality-based algorithmic points system further refines the collaborative filtering process, rewarding users for high-quality contributions and fostering a community of trust. As a result, decentralized social networks powered by Newcoin offer a more transparent, user-centric alternative to traditional platforms, promoting a more authentic and meaningful digital social experience.

Algorithmic Blockspace Arbitration on Ethereum[36]

In addressing the inefficiencies of blockspace allocation during periods of network congestion, Newcoin introduces a novel approach that prioritizes transactions based on the actual value contributed to the network. By leveraging its advanced algorithmic consensus framework, Newcoin enables system contracts to identify and reward genuine value creators, ensuring that essential transactions are processed efficiently. This model contrasts sharply with current mechanisms that often favor high-paying transactions, irrespective of their contribution to network utility. Newcoin's method reduces the undue advantage of MEV bots and aligns network resources with activities that foster real economic and social value, demonstrating the potential of algorithmic consensus to create a more equitable digital economy.

Retroactive Public Goods Funding RPGF[37]

The Agent Graph approach of Newcoin significantly enhances the discernment of value creation for Retroactive Public Goods Funding (RPGF) by establishing a nuanced framework where the contributions of individual agents are evaluated based on the quality and impact of their input. In a use case scenario, consider a decentralized educational platform that relies on community contributions to generate and curate learning content. By integrating Newcoin, the platform can automatically assess the value of each contribution through base points, which reflect the collective judgment of the community's expertise and engagement levels. High-quality contributions that receive positive feedback from knowledgeable community members would earn more base points, thereby gaining visibility and prioritization in RPGF allocations. This mechanism ensures that funding is dynamically directed towards contributors who offer the most substantial benefits to the community, fostering an environment where valuable public goods are continuously recognized and supported.

Evolutionary AI Through Peer-to-Peer Pipeline[38]

Newcoin's protocol offers a new approach to training Evolutionary Foundational Models (EFMs) in AI, focusing on high-fidelity, curated feedback loops that reflect a wide spectrum of human cognition and expertise. This method contrasts sharply with traditional models trained on noisy, unfiltered web data, prone to biases and inaccuracies. By leveraging a structured feedback graph enriched with domain-specific insights and contextual nuances, Newcoin enables AI models to iteratively query and learn from the most informative data points. This not only boosts learning efficiency by concentrating on valuable interactions but also minimizes the embedding of societal biases. Incorporating expertise levels into the feedback mechanism ensures that the impact of feedback on the model's learning trajectory aligns with the provider's relevance and depth of expertise, allowing for the development of AI systems that are proficient in complex, specialized tasks. Such an adaptive learning process, supported by continuous updates with new feedback, promises to evolve EFMs in parallel with human knowledge, societal norms, and ethical standards, marking a significant leap towards creating more responsive, responsible, and human-centric AI technologies.

---

[35] Resnick, P., & Varian, H. R. (1997). "Recommender Systems." Communications of the ACM, 40(3), 56-58.
[36] Buterin, V. (2021). "A Flexible Design for Funding Public Goods." Ethereum Blog.
[37] Weyl, E. G., Hitzig, Z., & Liberman, V. (2019). "A Radical Proposal for Private Governance." RadicalxChange.
[38] Stanley, K. O., Clune, J., Lehman, J., & Miikkulainen, R. (2019). "Designing Neural Networks through Neuroevolution." Nature Machine Intelligence, 1, 24-35.

Algorithmic NFT Markets

Algorithmic NFT Markets leverage Newcoin's decentralized machine learning and algorithmic consensus to autonomously moderate and rank NFTs, ensuring integrity and promoting quality within the ecosystem. By analyzing transaction histories, social signals, and creator reputations, this system dynamically evaluates NFTs, rewarding genuine creativity and community engagement. Creators must attain a specific score, reflecting their Web3 contributions, to mint NFTs, aligning incentives with real value creation. This approach fosters a transparent, meritocratic marketplace, enhancing trust and innovation in the digital art space.

Decentralized AGI Alignment

By amalgamating data from diverse interactions across the network, Newcoin facilitates the training of AI models that are attuned to the collective preferences and values of the community. This approach not only democratizes the development of AI but also ensures that AGI systems evolve in a manner that is inherently aligned with human interests[39]. The network intelligence generated through Newcoin's consensus mechanism acts as a foundational layer for AGI development, steering it towards outcomes that reflect the will and welfare of the global community.

[39] Bostrom, N. (2014). "Superintelligence: Paths, Dangers, Strategies." Oxford University Press.