Codatta: Decentralized Knowledge Layer for AI

The Decentralized Protocol Aligning Human Expertise and AI Advancement

Abstract

Codatta is a blockchain-based decentralized knowledge infrastructure designed as an attempt to revolutionize how data is sourced, validated, and monetized for AI systems by addressing the shift from computational to knowledge bottlenecks in AI development. Through on-chain data management with cryptographic verification, a DID-based reputation system for persistent professional identities, and royalty-based reward mechanisms, the platform enables transparent data lineage tracking, fair compensation models, and democratized access to specialized knowledge. The underlying XnY Network architecture supports various applications including human intelligence platforms, evaluation systems, and data ownership marketplaces, allowing domain experts without technical AI expertise to participate in the AI economy while helping developers build more capable systems through access to higher-quality specialized information—ultimately fostering innovation with fair value distribution across the ecosystem.

1. Introduction

1.1 The Critical Problem in AI Development

The AI revolution has transformed industries across the globe, yet a fundamental challenge remains unaddressed: the sourcing, ownership, and fair compensation for high-quality data that powers artificial intelligence. As AI systems advance in capability, the demand for specialized, domain-specific data has increased dramatically, creating an unsustainable ecosystem. Knowledge contributors remain undervalued despite their expertise being the foundation of AI advancement. Centralized data markets create artificial barriers that slow innovation and concentrate benefits in the hands of a few large players. Domain expertise lacks proper valuation mechanisms, significantly limiting incentives for specialized knowledge sharing across critical fields. Meanwhile, smaller innovators face prohibitive costs when accessing high-quality training data, preventing democratized participation in AI development. The persistent misalignment between data creators and AI developers generates systemic inefficiencies that ultimately slow progress and concentrate value unfairly.

Codatta addresses these challenges by reimagining the relationship between data, its creators, and AI systems through blockchain technology. Unlike traditional centralized data marketplaces that enforce rigid compensation models and opaque ownership structures, Codatta establishes a decentralized knowledge layer that democratizes AI development while ensuring fair attribution, compensation, and accessibility across the entire ecosystem.

1.2 Our Vision

Codatta envisions a future where knowledge becomes a tradable, verifiable asset with transparent provenance, accelerating AI advancement while democratizing its benefits. By establishing a decentralized knowledge infrastructure, we unlock specialized domains previously inaccessible to AI systems due to misaligned incentives, enabling domain experts to receive fair, ongoing compensation proportional to the value they create. Our protocol transforms data quality bottlenecks into opportunities for collaboration, allowing foundation models to rapidly adapt to specialized applications through targeted expert contributions. This approach not only enhances AI performance in complex domains but also creates new economic opportunities for knowledge contributors globally—from doctors and scientists to developers in emerging markets—without requiring technical expertise in machine learning. Through blockchain-based attribution and automated royalty distribution, Codatta ensures that as AI applications generate value, that value flows back to those whose knowledge enabled their creation, resolving the tension between rapid technological advancement and equitable benefit distribution. By embedding principles of transparency and fair compensation directly into the protocol's architecture, we transform AI development from competition for scarce resources into a collaborative ecosystem where proper economic alignment accelerates progress while ensuring its benefits are broadly shared.

2. Understanding AI, Data, and Value Creation

2.1 The Fundamental Role of Data in AI Systems

Unlike traditional software systems that operate on explicit programming logic, machine learning and AI systems derive their capabilities from patterns extracted from training data. This fundamental difference transforms data from a mere input resource into the core of AI value creation.

Machine learning models utilize optimization algorithms to iteratively adjust internal parameters (weights) by minimizing a loss function—a mathematical representation of prediction error. The goal is to find parameter configurations that best capture the underlying patterns in the training data, represented as input-output pairs (x, y). These patterns ideally reflect the actual relationships in the system generating the data.

The measure of true intelligence in these systems is generalization—the ability to make accurate predictions on previously unseen data. A model that merely memorizes training examples demonstrates poor generalization and limited intelligence. In contrast, a model that extracts meaningful patterns can successfully predict outcomes for novel inputs, exhibiting genuine intelligence.

It's important to note that in classical machine learning, this generalization is typically regional or task-specific. One model is designed to serve a specific, narrowly-defined task well—such as identifying human faces, predicting the default likelihood of loans, or calculating the probability of user clicks on advertisements. This task-specific generalization differs significantly from the broader capabilities of modern AI systems that attempt to generalize across domains.

This generalization capability depends critically on the quality, diversity, and representativeness of training data. The data provides the essential knowledge from which AI models learn patterns and develop predictive capabilities. Without high-quality data, even the most sophisticated AI architectures fail to achieve meaningful intelligence, regardless of whether the goal is narrow task-specific performance or broader cross-domain capabilities.

2.2 Large Language Models: Data's Evolving Role

Large Language Models (LLMs) exemplify the transformative potential of data-driven AI systems. Their development process illustrates the evolving relationship between data and model capabilities:

Pre-training Stage: Transformer-based LLMs consume vast quantities of text data scraped from the internet. After data processing (including deduplication and filtering), these models learn through auto-regressive training—predicting the next word given preceding context. This process creates a statistical representation of language patterns that serves as a distributed memory of human knowledge (up to the temporal cutoff of the training data).

The intuition behind this approach is that language inherently encodes human knowledge, reasoning patterns, and conceptual relationships. By learning to predict language patterns, LLMs implicitly absorb the knowledge embedded within text corpus, enabling them to generate contextually appropriate continuations that reflect human-like understanding. This learning process enables the model to develop a nuanced representation of knowledge across domains, from factual information to reasoning patterns and cultural concepts—all derived from the statistical patterns within the training data.

Post-training Stage: After pre-training, models undergo several critical post-training stages that further refine their capabilities:

- **Supervised Fine-Tuning (SFT):** The initial fine-tuning phase uses carefully curated datasets featuring high-quality instruction-response pairs. This process aligns the model's capabilities with desired behavior and improves performance on targeted tasks. SFT transforms a general language prediction model into an instruction-following assistant by learning the patterns of helpful, harmless responses.
- **Alignment and Safety Training:** Models then undergo specialized training with human feedback to ensure they align with human preferences and values. This includes:
    - Reinforcement Learning from Human Feedback (RLHF) where models are optimized based on human evaluations of response quality
    - Constitutional AI approaches that establish guardrails for model behavior
    - Specialized datasets to mitigate unwelcome behaviors such as hallucination, bias, or harmful outputs

Reinforcement Learning Stage: For models requiring stronger reasoning capabilities, reinforcement learning techniques enable the model to generate additional training data through self-improvement. By spending more compute time generating and evaluating responses, the model develops more sophisticated problem-solving strategies and improves its ability to generalize to unseen situations.

2.4 Domain Specialization Through Adaptation with Domain-Specific Data

Despite their impressive capabilities, out-of-the-box foundation models often struggle with specialized domains and tasks. For example:

- In clinical medicine, general foundation models frequently misinterpret specialized terminology, provide outdated treatment recommendations, and fail to adhere to domain-specific protocols
- Legal language models may misunderstand jurisdiction-specific precedents, misinterpret complex clauses, or make fundamental errors in applying legal doctrines
- Financial analysis models often lack understanding of industry-specific metrics, regulatory frameworks, and appropriate risk assessment methodologies
- In scientific research domains, foundation models may generate plausible-sounding but fundamentally incorrect explanations of specialized phenomena

Research has consistently demonstrated that with remarkably few high-quality domain-specific examples (often just hundreds or thousands rather than millions), these performance gaps can be dramatically reduced. Studies show that targeted fine-tuning can improve domain-specific task performance by 30-70% while reducing error rates in specialized contexts by up to 90%.

After the development of foundation models through the stages above, further specialization becomes possible through efficient adaptation techniques:

Parameter-Efficient Fine-Tuning: Techniques like LoRA (Low-Rank Adaptation) or QLoRA (Quantized Low-Rank Adaptation) enable efficient domain adaptation without retraining the entire model. By modifying only a small subset of parameters, these approaches make specialization economically viable for smaller organizations with limited computational resources.

Domain-Specific Adaptation: Open-source foundation models (such as Alibaba's Qwen, DeepSeek's R/V series, or Meta's Llama) can be efficiently adapted to specialized domains through targeted fine-tuning with domain-specific data, creating:

- Specialized LLMs for legal, medical, or financial applications
- Vision-Language Models (VLMs) for multimodal understanding in specific contexts
- Customized diffusion models for domain-specific creative generation
- Adapted robotics systems for particular physical interaction scenarios

Knowledge Distillation: To improve deployment efficiency, specialized knowledge from domain-adapted large models can be distilled into much smaller models. This process creates specialized tiny LLMs that maintain performance on targeted tasks while dramatically reducing computational requirements. Since much of the original capacity is unnecessary for specific tasks, distillation enables practical deployment without meaningful performance loss in the targeted domain.

2.3 Scaling Laws and the Critical Data Bottleneck

The Three Pillars of AI Advancement

Research has established that AI progress rests on three fundamental pillars, each playing a distinct and critical role:

1. Model Architecture and Learning Algorithms: Model architectures and learning algorithms determine the efficiency with which AI systems extract knowledge from data. Innovations like transformers, attention mechanisms, and optimization techniques have dramatically improved this efficiency, enabling models to learn more effectively from the same amount of data. However, architecture alone cannot create knowledge—it can only extract what exists in the training data.

2. Data, The Knowledge Repository: Data serves as the actual repository of knowledge from which AI systems learn. The quality, diversity, and representativeness of this data fundamentally determine the ceiling of what any AI system can achieve. Even the most sophisticated architecture cannot transcend the limitations of its training data. Data quality establishes both the upper bound of performance and the generalizability of the resulting model.

3. Computational Power: Computing resources fuel the execution of the learning process, allowing AI models to evolve through processing increasingly large datasets. While computational capacity enables larger models and more extensive training, it cannot compensate for fundamental limitations in data quality or representativeness.

The Evolution of Scaling Laws

The relationship between these pillars is formalized in scaling laws, which initially suggested that model performance improves predictably with increases in model size, data volume, and computation. However, the AI field has witnessed a significant evolution in how these laws apply:

Pre-training Scaling (2018-2022): Early scaling focused primarily on expanding model size and ingesting more internet data. This approach yielded dramatic improvements but eventually encountered diminishing returns as models consumed most readily available high-quality data.

Test-time Scaling (2022-Present): As high-quality data became scarce, emphasis shifted to enhancing model capabilities during inference rather than training. Techniques like Chain-of-Thought reasoning, recursive self-improvement, and retrieval augmentation enabled models to perform better without requiring proportionally more training data.

The Fundamental Bottleneck: Specialized Knowledge

Despite these advances in test-time scaling, a fundamental limitation has emerged: the finite nature of existing high-quality knowledge. The accumulated knowledge of humanity—developed through thousands of years of human experience, billions of people's insights, and countless experiments—cannot be fully simulated or generated artificially within any reasonable timeframe or energy constraint.

This limitation creates a critical bottleneck in AI advancement: specialized knowledge, particularly well-structured examples featuring questions, reasoning processes, and answers, cannot be generated solely through algorithmic means. Instead, this knowledge must be contributed by domain experts and non-experts across the globe.

While the technical capability to incorporate such knowledge exists, current economic models fail to incentivize its large-scale contribution. The next frontier in AI advancement therefore depends not only on architectural innovations or computing power, but also on creating effective mechanisms to reward knowledge contribution at scale—enabling a massive collaborative effort to unlock specialized knowledge across domains.

This shift fundamentally transforms the economics of AI development, moving from a model dominated by technical resources to one centered on knowledge mobilization through proper incentive alignment.

3. Survey on Human Intelligence Platform

3.1 Introduction to Current Human Intelligence

Workflow of Data Labelling

Human intelligence platforms (sometimes called "crowdsourcing platforms") are online marketplaces that connect businesses needing data labeling and other human judgment tasks with a global workforce ready to complete these tasks. Notable examples include Amazon Mechanical Turk, Scale AI, Appen, Toloka, and Clickworker. These platforms play a crucial role in the AI development ecosystem by generating the high-quality labeled data needed to train machine learning models.

The data labeling workflow on human intelligence platforms follows a streamlined four-stage process. Initially, businesses define their labeling requirements by creating detailed instructions, quality standards, and pricing structures based on task complexity. These tasks are then broken down into smaller units (HITs) and distributed to qualified workers based on their skills, location, or performance history. Workers complete these assignments according to instructions, after which businesses review submissions using quality control mechanisms like gold standard questions, consensus methods, and statistical analysis to verify accuracy. Finally, approved work is compensated at predetermined rates, the labeled data is aggregated and formatted to specifications, and then integrated into AI training pipelines where it becomes the foundation for machine learning model development.

Best Practices for Quality Management

Effective data quality management on human intelligence platforms requires a comprehensive approach that balances quality with cost considerations. Businesses achieve optimal results by providing clear, detailed instructions with visual examples and defined protocols for edge cases, while maintaining accessible communication channels for worker questions. Quality assurance typically employs multi-layered strategies including pre-qualification testing, deliberate redundancy where multiple workers label the same items, and statistical anomaly detection to identify problematic submissions. The process benefits from iterative improvement through initial pilot testing, soliciting worker feedback, and continuous refinement of criteria based on observed results. While essential for quality, these practices introduce higher costs: redundant labeling multiplies expenses, qualification testing reduces the available workforce, statistical validation requires additional technical infrastructure, and maintaining worker engagement through competitive compensation and meaningful feedback increases per-task expenditures. Nevertheless, these investments typically yield higher-quality data that reduces costly downstream errors in AI model development.

3.2 Limitations and Potential Improvements

Despite their widespread adoption, human intelligence platforms face significant challenges that affect their effectiveness, efficiency, and social impact. Understanding these limitations is crucial for businesses seeking to optimize their data labeling strategies and for the development of more sustainable approaches to human-in-the-loop AI development.

Data Quality Limitations

Human intelligence platforms face persistent quality control issues despite following best practices. Highly-rated workers fail basic attention checks up to 20% of the time, adding noise to training data. Complex labeling tasks produce inconsistent interpretations between workers, particularly without clear right/wrong answers. General-purpose platforms rarely have workers with specialized expertise in technical fields like medicine or law. Quality verification typically uses limited sampling instead of comprehensive review, creating blind spots. Poor documentation makes tracing errors or biases difficult when they emerge in models.

Worker Motivation and Economic Challenges

Economic structures of these platforms undermine data quality and worker well-being. Platforms like Mechanical Turk pay median wages around $2-3 per hour—below minimum wage in many countries—directly affecting motivation and quality. One-time payments disconnect compensation from the long-term value created, while providing few opportunities for advancement. This leads to high turnover rates and workforce instability. The system often exploits global wage disparities by routing tasks to lower-income regions without adequate protections.

Cost Efficiency and Hidden Expenses

Despite appearing cost-effective, human intelligence platforms have significant hidden costs. Achieving acceptable quality requires higher pay rates and redundant labeling, substantially increasing expenses. Platform management demands considerable internal resources for task design, quality monitoring, and dispute resolution. Poor initial results often require multiple labeling rounds, multiplying costs. As projects grow, quality management becomes exponentially more complex and expensive. Most critically, low-quality labeled data creates downstream technical debt through model errors that may only appear after deployment.

Social Impact and Ethical Considerations

The human intelligence ecosystem raises serious ethical concerns about fairness and worker dignity. Workers' essential contributions become invisible in final AI products—termed "ghost work"—despite being fundamental to their creation. Contributors surrender rights to their work without knowing how it will be used. Platform policies favor requesters over workers, with limited recourse for unfair rejections. Content moderation can expose workers to disturbing material with minimal psychological support. Most platforms treat workers as interchangeable resources rather than skilled contributors.

3.3 Next Generation of Human Intelligence Platform

Enhancing Data Quality

Specialized expertise platforms represent a fundamental shift from general-purpose crowdsourcing toward communities focused on specific domains such as medical imaging, legal document analysis, or specialized content moderation. Evidence shows domain-specific platforms achieve 40% higher accuracy rates on technical tasks compared to general platforms (Chen et al., 2023). This improvement stems from stronger qualification processes that verify worker knowledge before task assignment. In a comprehensive study across five industry sectors, Wong & Martinez (2024) found that domain-specific workers were three times more likely to identify subtle edge cases.

Documentation of decision rationales involves systematic recording of why workers made specific labeling choices rather than just capturing the final decisions. Platforms that implemented decision tracking reduced error investigation time by 65% in recent case studies (Johnson Research Group, 2024), enabling faster model debugging and refinement. The Stanford ML Governance Initiative (2023) documented how annotation rationales significantly improved model explainability across 12 enterprise AI implementations.

Hybrid AI-human systems combine automated labeling with human verification in orchestrated workflows where machines handle routine cases and humans focus on exceptions. Early adopters report 30% cost reduction while maintaining quality by using AI for routine labeling and human judgment for complex cases (Schmidt & Lee, 2024). This symbiotic approach reduces worker fatigue by eliminating repetitive tasks while preserving human oversight where it matters most. Google Research's study of 50 enterprise data labeling projects found hybrid systems reduced overall annotation time by 47% (Alvarez et al., 2023).

Reimagining Worker Engagement and Compensation

Revenue-sharing models restructure compensation by connecting worker earnings to the downstream value created by AI systems trained on their labeled data. Platforms experimenting with compensation tied to data value report 78% higher worker retention and 45% quality improvement (Data Labor Alliance, 2024). This direct connection to long-term impact motivates workers to prioritize accuracy over speed. Microsoft's experimental Fair Crowds program demonstrated that revenue-sharing incentives produced 23% more precise annotations than fixed-price schemes (Patterson & Kim, 2023).

Skill advancement pathways create structured progression routes for workers to develop specialized expertise and increase their earnings potential over time. Organizations implementing tiered expertise levels with corresponding pay increases see 3x longer worker engagement (Harris Future of Work Institute, 2024). These pathways allow workers to develop specialized skills and earn recognition for their expertise. In a longitudinal study of 1,200 crowdworkers, Torres et al. (2023) found that career advancement opportunities were the strongest predictor of long-term platform commitment.

Worker-owned models restructure platform governance to give contributors partial ownership and decision-making power, either through cooperatives or distributed governance structures. Cooperative platforms report 52% higher worker satisfaction scores and consistently outperform traditional platforms on quality metrics (Distributed Work Cooperative, 2024). Treating workers as partners rather than resources produces better data while supporting dignified work arrangements. The MIT Digital Economy Lab (2023) documented three platform cooperatives that achieved 35% higher annotation precision than comparable commercial alternatives.

Optimizing Cost Efficiency

Worker retention strategies focus on maintaining relationships with high-performing contributors rather than constantly recruiting and training new workers. Organizations investing in stable workforces report 40% lower management overhead and 25% fewer required corrections (Crowdsourcing Efficiency Consortium, 2024). The institutional knowledge retained in experienced workers translates directly to higher first-pass accuracy. Berkeley's study of enterprise crowdsourcing programs found that platforms with retention rates above 70% spent 62% less on quality management than those with high turnover (Wang & Patel, 2023).

Better collaboration tools encompass purpose-built software interfaces designed specifically for labeling efficiency, communication, and worker wellbeing. Platforms with optimized interfaces and collaboration features achieve 35% higher throughput rates for complex tasks (HCI for Crowdwork Initiative, 2024). These efficiency gains offset the higher costs of worker-friendly systems. Scale AI's redesigned interface reduced task completion time by 41% while improving accuracy by 12% according to an independent audit by the Data Systems Laboratory (Rodriguez et al., 2023).

Strategic quality control systems replace blanket verification with targeted approaches that focus review resources on high-risk submissions. Adaptive systems that allocate review resources based on risk assessment reduce QA costs by up to 60% without compromising quality (Quality Analytics Working Group, 2024). Many organizations now find that paying higher rates to fewer reliable workers ultimately costs less than managing many lower-paid contributors. The Cloud ML Benchmarking Consortium documented 22 case studies where targeted quality strategies reduced total project costs by 28-45% (Yamamoto et al., 2023).

Prioritizing Ethical Framework

Data provenance tracking establishes comprehensive records of who contributed to datasets, under what conditions, and for what purpose. Organizations implementing comprehensive tracking systems report 42% faster response to potential bias issues (AI Ethics Observatory, 2024). This transparency allows stakeholders to understand how labeled data influences model behavior. In a cross-industry survey, the Data Ethics Coalition (2023) found that transparent provenance was the strongest predictor of successful model governance and regulatory compliance.

Worker agency mechanisms give contributors more control over task selection, working hours, and content exposure. Platforms giving workers more control over task selection show 38% lower burnout rates and 27% higher quality scores (Labor Psychology Institute, 2024). This autonomy fosters healthier contributor relationships and sustained engagement. The International Labor Digital Rights Consortium's study of 18 platforms found that worker agency correlated strongly with both quality metrics and platform retention (Mehta & Robertson, 2023).

Comprehensive ethical standards establish clear guidelines covering fair compensation, reasonable content exposure limits, and recognition of workers' contributions. Organizations with comprehensive ethical frameworks report 45% fewer project disruptions and higher client satisfaction (Responsible AI Foundation, 2024). These standards covering fair treatment, content exposure limits, and proper attribution build sustainable ecosystems that benefit all stakeholders. The World Economic Forum's study of AI supply chains (2023) identified ethical standards as a key resilience factor, with standardized frameworks reducing project delays by 37%.

4. Codatta: A Decentralized Human Intelligence Protocol for the AI Economy

4.1 The Evolving Landscape of AI Data and Platform Limitations

The advent of large language models (LLMs) has fundamentally transformed the role of data in artificial intelligence development. As foundation models become increasingly sophisticated, the market dynamics have shifted dramatically: demand for basic labeling is declining, while advanced contributions carrying domain expertise or chain-of-thought reasoning are experiencing unprecedented growth. Domain experts who provide nuanced understanding and specialized insights have become the cornerstone of vertical AI applications, transforming general-purpose models into powerful domain-specific tools.

Despite this evolution, current human intelligence platforms—designed approximately a decade ago—continue to operate on centralized infrastructure and traditional business models ill-suited for the post-LLM era. As AI innovation becomes increasingly decentralized with numerous small teams building specialized applications, these legacy platforms face critical limitations that hinder progress. One-time payment models fail to align with the long-term value generated by domain expertise, with specialists receiving the same compensation structure as basic labelers despite creating significantly more enduring value. The lack of verifiable records for contribution quality and expertise creates information asymmetry where platforms struggle to identify high-value contributors, while genuine experts lack mechanisms to demonstrate and monetize their specialized knowledge.

Furthermore, traditional platforms maintain exclusive ownership of contributor networks and data assets, creating artificial scarcity and extracting disproportionate value. This centralization impedes innovation by restricting access to high-quality data for smaller developers. Current systems cannot accurately trace how specific contributions influence model performance, making fair value-based compensation models impossible to implement. Contributors also suffer from siloed reputation and expertise, unable to carry their established credentials across platforms, which forces redundant verification processes and fragments professional identity.

4.2 Codatta: Making AI Subscribe to Human Knowledge

Core Philosophy and Vision

Codatta introduces a paradigm shift through its decentralized human intelligence protocol. The core philosophy is revolutionary yet intuitive: making AI subscribe to human knowledge. Domain experts can earn long-term rewards by providing specialized knowledge that transforms foundation models into vertical AI applications with specific capabilities. This approach fundamentally realigns incentives across the AI development ecosystem, creating sustainable value flows that benefit all participants.

On-chain AI Data Management

The on-chain AI data management system establishes immutable contribution records that create transparent data lineage throughout the AI development process. This system incorporates privacy-preserving mechanisms that protect sensitive information while maintaining verifiability, allowing contributors to share valuable insights without compromising confidentiality. Cryptographic proofs validate data without exposing original content, and smart contract-enforced access controls follow programmable logic to ensure proper data utilization.

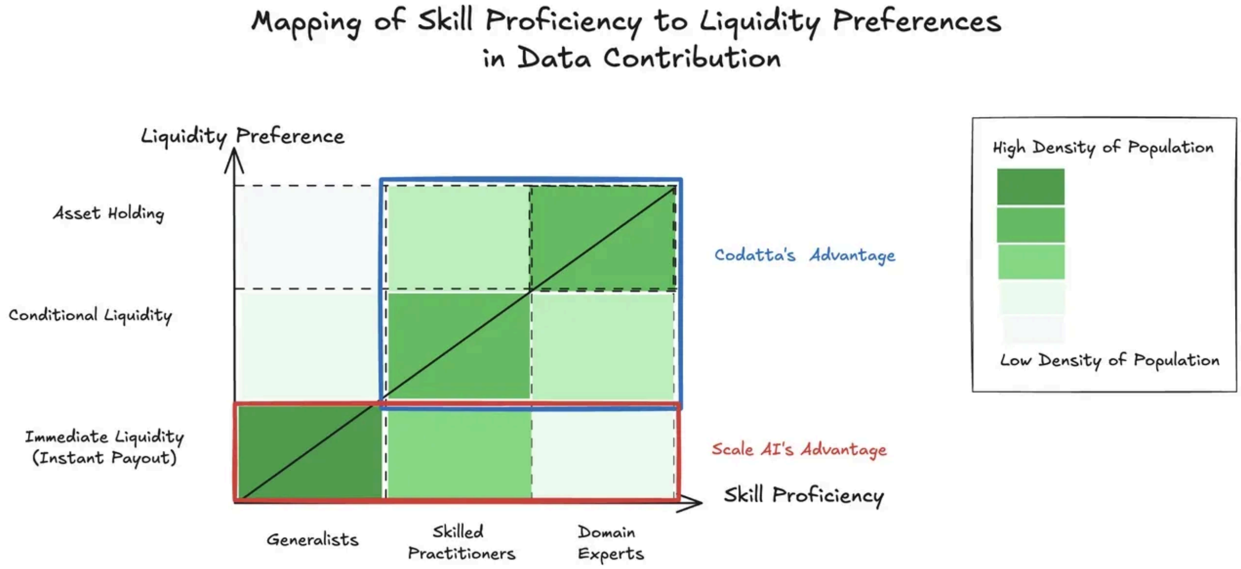
Significantly, Codatta recognizes that valuable data contributions can originate from both human experts and AI systems themselves. This hybrid approach acknowledges the emerging reality where AI tools assist human experts in data creation or where existing AI systems generate base insights that human experts refine and validate. By tracking contributions from both human and artificial intelligence sources, the protocol creates a more complete attribution framework that reflects the increasingly collaborative nature of knowledge production.

DID-based Reputation System

The protocol implements a robust DID-based reputation and credential system that creates persistent professional identities across the ecosystem. This system enables multi-dimensional expertise indexing for efficient contributor-task matching, while community-validated credentials reflect domain-specific capabilities. Contributors build transparent histories that enhance trust and improve retention rates, with performance metrics that incentivize quality contributions over mere quantity.

Royalty-based Reward System

Codatta's royalty-based reward system represents a fundamental innovation in how human intelligence is valued. On-chain training and inference attribution tracks value creation throughout the AI lifecycle, while smart contracts automatically distribute compensation based on actual usage. The system supports variable reward structures adaptable to different contribution types and domains, with time-locked incentives that encourage sustained quality and ongoing improvements. This creates a transparent value flow from AI deployment back to the knowledge contributors who made it possible.



Assetification of Datasets

The protocol also pioneers the assetification of datasets, transforming knowledge contributions into tokenized, transferable ownership rights. Secondary markets enable price discovery and provide liquidity options that compensate for the time-lagging nature of royalty-based models. Contributors can realize immediate value while maintaining long-term upside potential, creating investment opportunities in promising data assets that align incentives across the ecosystem.

4.3 XnY Network: Technical Architecture

Framework Foundation and Abstraction

The XnY network provides the technical foundation for Codatta's vision through a multi-chain abstraction that delivers the capabilities required for a decentralized human intelligence protocol. The XnY framework represents a fundamental abstraction where X represents samples or raw data inputs, while Y represents labels, annotations, or domain expert opinions. This elegant model allows the system to track complex relationships between data inputs and the human intelligence that transforms them into valuable AI training assets.

Flexible Domain-Specific Implementation

A key strength of the XnY framework lies in its flexible architecture that supports custom on-chain data pipelines for domain-specific applications. For example, a crypto AML intelligence platform could implement specialized annotation structures within the XnY network, mapping blockchain addresses to categorization labels and supporting evidence. The contribution record might encode relationships like [address, [categories, evidence]], creating transparent attribution for financial intelligence contributions while maintaining the cryptographic security guarantees of the underlying blockchain.

This flexibility extends to diverse domains with unique data requirements, from medical diagnostics to legal document analysis, each with their own specialized ontologies and relationship structures. The XnY framework adapts to these varying needs through customizable smart contracts that implement domain-specific business logic while maintaining cross-domain compatibility.

On-chain Contribution Records

Contribution records form the backbone of the system, encoded on-chain with critical metadata including contributor identifiers linked to decentralized identities, relationship mappings between samples and labels, precise timestamps for establishing provenance, and cryptographic hashes that reference the contributed data. These records also contain usage permissions and compensation terms that govern how the data may be utilized. The actual contributed data resides in decentralized storage solutions, with only references and metadata maintained on-chain, balancing transparency with scalability and privacy requirements.

Identity and Reputation Layer

The network implements a comprehensive identity layer through its DID-based credential and reputation systems. This layer enables verifiable credentials attesting to domain expertise and portable reputation scores that function seamlessly across the entire ecosystem. Contributors develop transparent histories accessible to all participants, facilitating expertise discovery and efficient task allocation. Trust networks emerge organically, enhancing collaboration quality and creating positive feedback loops that improve the overall ecosystem.

Staking Mechanism

The XnY network incorporates a robust staking mechanism that enhances security and trust within the ecosystem. Staking, a fundamental concept in blockchain systems, requires participants to lock up a certain amount of cryptocurrency as collateral, creating economic incentives for honest behavior. In traditional blockchain networks, staking helps secure consensus mechanisms by ensuring validators have "skin in the game." Within the XnY network, this mechanism is adapted to address the unique challenges of data quality and contributor accountability.

Reputation-linked staking forms a core component of the contributor verification system. Contributors can stake tokens to boost their reputation metrics, signaling commitment to quality work and domain expertise. This stake serves as collateral against performance, with partial slashing penalties applied for intentional error injection or demonstrably careless handling of assigned tasks. The slashing mechanism is governed by transparent rules and multi-party validation to prevent abuse, creating strong disincentives for low-quality or malicious contributions. As contributors build positive track records, they may qualify for reduced staking requirements while maintaining enhanced reputation scores, rewarding consistent high-quality participation.

The system also enables contribution-specific staking, where contributors can optionally stake tokens directly against specific data contributions. This mechanism allows contributors to signal exceptional confidence in particular submissions, providing data consumers with additional trust signals. These contribution-specific stakes remain locked until the data has been utilized without discovered errors for a predefined period, or they may be partially or fully slashed if significant errors are discovered and verified. This approach creates a powerful form of warranty for data quality, particularly valuable in high-stakes domains like financial intelligence, healthcare, or safety-critical systems.

By implementing these staking mechanisms, the XnY network creates economic alignment between contributor incentives and ecosystem quality requirements. The approach transforms abstract reputation metrics into concrete economic commitments, enhancing trust between anonymous or pseudonymous participants without requiring traditional centralized verification systems. This cryptoeconomic design reinforces the protocol's core value proposition of making AI subscribe to human knowledge by ensuring that knowledge meets rigorous quality standards.

Transparency and Governance

Throughout the data creation lifecycle, the XnY network provides unprecedented transparency. Auditable authentication processes verify contributor identities, while fair attribution mechanisms ensure proper credit for all contributions. The system recognizes valuable inputs through sophisticated metrics, maintains clear property rights through ownership identification, and tracks utilization throughout the entire data lifecycle. This comprehensive transparency creates trust between all participants in the ecosystem.

Through this architecture, Codatta establishes a new paradigm for human intelligence in AI development - one where contributors receive fair compensation proportional to the value they create, developers gain access to high-quality specialized knowledge, and the entire ecosystem benefits from aligned incentives and transparent operations.

5. Token Utility in Codatta

5.1 The Role of Tokens in Successful Protocols

Tokens have become the cornerstone of successful blockchain protocols, driving adoption, aligning incentives, and enabling new economic models. Ethereum's native token (ETH) fundamentally transformed how we think about decentralized applications by creating a unified economic layer that powers computation across thousands of applications. Beyond simply paying for transactions, ETH became a store of value and the backbone of an entire financial ecosystem. Similarly, Compound's COMP token revolutionized decentralized finance by shifting from a purely transactional model to one where governance and ownership are distributed to actual users of the protocol. This innovation created unprecedented alignment between users, developers, and investors.

The most successful token designs share key characteristics: they capture the value created within their ecosystems, they align the incentives of diverse stakeholders, and they create sustainable economic activity rather than merely facilitating speculation. These principles have guided the development of XNY, Codatta's native token, which builds upon these proven models while addressing the unique requirements of a decentralized knowledge layer.

5.2 Token Utility: Where XNY Is Spent

Transaction Gas Fees

XNY serves as the mandatory payment method for all on-chain operations, including data contributions, verification processes, and ownership transfers. This requirement serves multiple critical functions for the network. Gas fees prevent spam attacks and ensure only legitimate transactions are processed, creating a baseline security measure. The fees can be dynamically adjusted based on the complexity of data verification workflows, which means more resource-intensive verifications command proportionally higher costs. This creates economic alignment as contributors must have financial "skin in the game" when adding to the knowledge base. The collected fees compensate network participants who validate and process transactions, creating a sustainable economic loop. For example, submitting a complex dataset with custom AI verification requirements would command higher gas fees than a simple text contribution, reflecting the computational resources needed for proper validation.

Data Access and Ownership Transfers

XNY functions as the primary medium of exchange when interacting with data assets on the platform. When users purchase full or partial ownership rights to datasets, they do so using XNY tokens, creating direct value flow to the original creators. Similarly, accessing permission-gated data resources requires token expenditure, with prices reflecting the value and rarity of the knowledge being accessed. When licensing knowledge assets for specific use cases, the licensing fees are denominated in XNY, allowing for frictionless transactions across different knowledge domains. This creates a direct economic relationship between data creators and consumers without requiring intermediaries for settlement, reducing overhead and increasing the efficiency of knowledge transfer.

Staking Mechanism

Staking XNY tokens provides both security for the network and benefits for the token holders. Validators must stake substantial tokens to participate in network consensus as orchestration nodes, ensuring they have economic incentives aligned with honest validation. The Codatta DID system uses stake size as one factor in reputation building, where higher stakes correlate with higher trust levels. This creates natural incentives for reputable participants to maintain larger stakes. Perhaps most importantly, the security of the entire system is reinforced by the possibility that staked tokens can be slashed for malicious behavior. When participants engage in fraud or other harmful activities, they risk losing their entire stake, making attacks economically irrational for all but the most well-funded adversaries. The staking mechanism ensures that those with the most at stake economically are those who gain the most influence within the system, aligning power with responsibility.

Governance Participation

XNY holders gain voting rights proportional to their holdings, allowing them to shape the future of the platform. Token holders can propose changes to network parameters, adapting the system to evolving needs and challenges. They vote on protocol upgrades that enhance functionality, security, or efficiency. Resource allocation decisions for ecosystem development are made through token-weighted governance, ensuring that investment flows to the most valuable areas. Verification standards and requirements evolve through governance decisions, keeping quality high while adapting to new technologies. This governance system ensures that those most invested in the platform's success make the decisions that guide its development, creating long-term alignment between individual incentives and collective outcomes.

5.3 Token Acquisition: How XNY Is Earned

Data Contributions

The primary method of earning tokens is through valuable knowledge contributions to the network. Creating and submitting original, verified data represents the fundamental productive activity within Codatta. Contributors receive tokens proportional to the value they add to the collective knowledge base. Participants can also earn tokens by verifying others' submissions, providing the crucial service of data validation that maintains quality standards. Some contributors specialize in enhancing existing data through enrichment, correction, or contextualization, earning rewards for the added value they create. Throughout all these contribution types, the amount of XNY earned correlates directly with the quality, uniqueness, and utility of the contributed data. This creates a sustainable economic model where value creation is rewarded with token issuance.

Bounty Hunting

The integrity of data within Codatta is maintained partly through economic incentives for identifying problems. Participants can earn significant XNY rewards by identifying fraudulent or erroneous submissions that might otherwise damage the ecosystem's reputation. Reporting malicious actors creates a distributed security system where all participants become potential guardians of data quality. When users successfully challenge incorrect data through formal verification processes, they receive compensation for their vigilance. In many cases, the reporter receives a portion of the slashed tokens from the offending party's stake, creating a powerful economic incentive for maintaining data integrity. This bounty system transforms security from a cost center to an opportunity for participants, aligning individual rewards with collective benefits.

Staking Rewards

Those who stake XNY tokens earn passive income through multiple mechanisms designed to reward long-term commitment to the network. Interest payments distributed from network transaction fees flow to stakers, creating a steady income stream proportional to their commitment. The reward structure incorporates consideration of both stake size and duration, encouraging long-term locking of tokens rather than speculative trading. Some validation tasks offer bonus incentives to stakers who participate, creating additional earning opportunities beyond basic interest. This reward system creates a virtuous cycle where long-term holders are compensated for maintaining network security and liquidity, stabilizing the token economy and reducing volatility.

5.4 Integration With Frontier Tokens

While XNY serves as the native network token, individual Frontiers (specialized knowledge domains) may issue their own tokens that interact with the core XNY system. These domain-specific tokens can represent ownership shares in particular data portfolios, functioning similar to specialized index funds for knowledge assets. Frontier tokens often provide specialized access rights to domain-specific resources, creating additional utility within their ecosystems. Governance participation within specific knowledge domains may require these specialized tokens, allowing for domain-specific decision-making while the broader platform governance uses XNY. The relationship between XNY and Frontier tokens creates a federated economic system where specialized knowledge domains maintain autonomy while benefiting from the shared infrastructure and liquidity of the main network.

5.5 Protocol Revenue Generation and Distribution

Codatta's economic infrastructure creates multiple sustainable revenue streams that support the protocol's growth and reward its participants. As a facilitator of domain-specific data creation, Codatta generates revenue through several key mechanisms that align incentives across the ecosystem.

The primary revenue source comes from transaction fees collected across the network. Each time users submit new data, verify existing contributions, or perform ownership transfers, Codatta collects a portion of the gas fees. This fee structure is calibrated to ensure sufficient compensation for validators while maintaining competitive pricing. The revenue sharing model intelligently distributes these fees, with verification contributors receiving payments proportional to their efforts on specific data topics. This targeted revenue sharing ensures that validators specialize in domains where they have expertise, improving both efficiency and quality.

Data demanders, particularly generative AI companies seeking high-quality training data, represent another significant revenue source. When these entities reward data contributors with stablecoins or other liquid tokens, Codatta applies a variable fee structure based on the resources utilized in sourcing and labeling the data. Projects requiring intensive curation, specialized verification, or rare data types command premium rates, while more standardized data collection efforts benefit from lower fees. This dynamic pricing model ensures that Codatta captures appropriate value while remaining competitive across different data verticals.

Ownership transfers of data assets constitute the third major revenue stream. Each time data ownership changes hands, whether through direct sales, licensing agreements, or fractional ownership models, Codatta collects a transaction fee. This creates ongoing revenue from data assets long after their initial creation, allowing the protocol to benefit from the increasing value of high-quality datasets over time.

All revenue collected flows back to the Codatta Foundation, which manages these funds with transparency and strategic focus. A significant portion is allocated to staking rewards, creating strong incentives for token holders to secure the network and promote long-term participation. By channeling revenue into staking rewards, Codatta creates a self-reinforcing ecosystem where success breeds further success; higher protocol revenue leads to better staking returns, which attracts more reputable data contributors, ultimately improving data quality and driving more usage.

This comprehensive revenue model creates sustainable economics that balance rewarding participants, funding ongoing development, and creating long-term value for token holders. By capturing value at multiple points in the data lifecycle while maintaining competitive pricing, Codatta establishes a foundation for sustained growth in the decentralized data economy.

6. Applications Built with Codatta

Codatta's fundamental capabilities create a powerful foundation for AI data management and ownership. The on-chain transaction record system ensures every data contribution, modification, and usage is permanently documented with cryptographic verification. The DID-based reputation system establishes verifiable identities for all participants, enabling trust through transparent history and credentials. These building blocks are complemented by smart contract-powered ownership attribution and decentralized storage integration, allowing for complex data governance while maintaining security and privacy. The following section explores the diverse applications and use cases that can be built upon these foundational elements, demonstrating how Codatta's architecture enables entirely new paradigms for human-AI collaboration.

6.1 Human Intelligence Platform

Codatta's human intelligence platform revolutionizes the data creation and AI training workflow through a comprehensive, transparent system built on Web3 principles. The end-to-end workflow begins with domain definition, where creators establish structured data schemas and taxonomies that define the parameters for data collection. These schemas specify the exact format, attributes, and relationships required for data points, while smart contracts automate governance of the domain, ensuring all contributions adhere to defined standards.

Contributor qualification forms the next critical stage, as participants must meet domain-specific requirements before contributing. Qualification may include demonstrating expertise, completing training, or passing assessment tests, with all qualification status recorded on-chain to create verifiable credential systems that build trust throughout the network.

Once qualified, contributors can submit data samples following the domain schema, with each sample potentially receiving multiple labels from different qualified contributors. This redundancy in labeling improves quality and allows for consensus mechanisms, while contributors maintain partial ownership of their data contributions, incentivizing high-quality submissions.

Every aspect of data creation is recorded on-chain, creating an immutable audit trail that defines co-ownership relationships between domain creators and contributors. The complete data can be reconstructed by integrating these on-chain records with content stored in decentralized storage systems, ensuring data provenance remains fully transparent and traceable throughout its lifecycle.

When data is used to train AI models, proof-of-training protocols verify and record this usage through cryptographic proofs that demonstrate specific data incorporation into training. This creates an unbroken chain of attribution from data to model, enabling fair compensation and recognition.

Deployed models track inference serving, attributing each inference back to the underlying data and distributing credits among all contributors: domain creators, data providers, labelers, and verifiers.

Attribution mechanisms can be defined through smart contracts or machine learning algorithms that measure different contributions to particular inferences, acknowledging that models are built from large collections of data points.

6.2 Trustworthy Evaluation and Benchmarking

Traditional centralized evaluation platforms face significant challenges with manipulation and trust. Codatta addresses these issues through comprehensive transparency mechanisms. Evaluators maintain corresponding on-chain accounts containing verifiable credentials including geographic location and connections to external platforms like Twitter and LinkedIn. Their past evaluation activities become publicly accessible, allowing anyone to verify their expertise and potential biases.

The system categorizes evaluators as "experienced" or "new," enabling segmented rankings that reveal attempts at manipulation. Suspicious patterns across multiple accounts can be identified through similarity analysis, making coordinated manipulation attempts evident. This transparency creates a self-regulating ecosystem where bad actors are quickly identified.

All evaluation feedback is permanently recorded on-chain, preventing tampering or post-hoc modifications that plague centralized systems. The public can independently audit rankings and question assessments, verifying the integrity of results without depending on a central authority. This radical transparency builds higher levels of trust in evaluation outcomes, addressing a critical weakness in current AI benchmarking.

Community governance mechanisms determine evaluation standards through democratic processes rather than centralized decision-making. Token holders participate in protocol upgrades and benchmark designs, ensuring the system evolves to meet changing needs. Incentive structures reward honest participation and penalize manipulation attempts, aligning economic interests with system integrity.

Through these mechanisms, Codatta transforms AI evaluation from a black-box process vulnerable to manipulation into a transparent, community-governed system that produces reliable results. Organizations can make informed decisions based on benchmarks with verifiable integrity, accelerating responsible AI development through trustworthy comparative analysis.

6.3 Marketplace for Trading Data Ownership

Codatta's marketplace enables the dynamic trading of data ownership rights, creating an ecosystem where contributors can monetize their data contributions through fractional ownership. Domain creators can acquire additional data rights or sell portions of their domains, while AI developers can purchase usage rights for specific datasets that meet their training requirements.

Smart contracts automatically enforce royalty distributions based on ownership percentages, eliminating disputes and ensuring fair compensation. Market mechanisms determine appropriate valuation of data based on quality, uniqueness, and utility, creating price discovery that reflects true value. Non-fungible tokens represent ownership shares, enabling fluid transfer and fractionalization that supports complex ownership arrangements.

Datasets created through the royalty model become true financial assets due to their entitlement to future revenue streams from downstream AI models trained with them. This fundamentally changes how data is valued—not just for its immediate utility, but as an investment with ongoing returns as AI systems generate value. The ownership of these datasets effectively represents access to a portfolio of AI products, since a single high-quality dataset can be utilized by multiple AI models or products across different applications. This multiplier effect increases the potential value of well-structured, high-quality data contributions.

The marketplace creates unprecedented liquidity for data assets, transforming them from static resources into dynamic investments. Contributors can build diversified portfolios of data assets across multiple domains, while developers gain access to specialized datasets previously unavailable. This creates a virtuous cycle where high-quality data receives greater rewards, incentivizing continuous improvement of the data ecosystem. As AI products succeed in the market, their success flows back to the original data contributors, creating alignment between data quality and long-term value creation.

7. Conclusion: Toward a Democratized Knowledge Economy

Codatta represents a fundamental reimagining of the AI data economy, addressing the critical disconnect between knowledge contributors and AI developers. By establishing a decentralized knowledge layer powered by the XnY network, we've created a system that transforms human expertise into verifiable, tradable assets with transparent attribution throughout the AI lifecycle. Our approach acknowledges that while computational resources and model architectures continue to advance, specialized knowledge remains the ultimate bottleneck in AI development—one that requires proper economic alignment rather than purely technical solutions.

Our phased development roadmap begins with establishing the core infrastructure in targeted high-value domains, expanding to comprehensive marketplace integration, and ultimately creating a mature ecosystem with standardized protocols for knowledge sharing across chains. This measured approach ensures sustainable growth while building the network effects necessary for widespread adoption. We recognize that democratizing AI development carries profound implications, particularly in how knowledge work is valued globally, and we commit to governance structures that prioritize accessibility, fairness, transparency, and diverse representation.

The vision outlined in this whitepaper cannot be realized through technical development alone. We invite domain experts across fields to contribute their specialized knowledge, AI developers to integrate our protocols ensuring proper attribution, data scientists to collaborate on effective value attribution mechanisms, and governance specialists to help design balanced stakeholder systems. Through this collaborative approach, Codatta aims to establish a knowledge economy that properly values expertise while accelerating responsible AI advancement—creating a future where technological progress and human flourishing advance together, and where the benefits of AI development flow back to those whose knowledge makes it possible.

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Glossary of Terms

Annotation: The process of adding metadata, labels, or explanatory notes to raw data to make it useful for training machine learning models. Annotations provide the ground truth that models learn from.

Artificial Intelligence (AI): Computer systems capable of performing tasks that typically require human intelligence, such as visual perception, speech recognition, decision-making, and translation.

Assetification of Datasets: The transformation of knowledge contributions into tokenized, transferable ownership rights.

Attribution Mechanisms: Systems for tracking how different contributions influence model performance and distributing credits accordingly.

Bias: In machine learning, a systematic error that causes a model to consistently produce results that favor certain outcomes over others, often reflecting societal or sampling biases in training data.

Blockchain: A distributed, immutable ledger technology that records transactions across multiple computers, enabling trustless verification of data without central authorities.

Codatta: A decentralized knowledge infrastructure designed to revolutionize how data is sourced, validated, and monetized for AI systems.

Cryptographics: The application of cryptographic techniques to secure and verify digital information, particularly in distributed systems like blockchains, ensuring data integrity and authentication.

Contributor Qualification: System for verifying expertise and capabilities of knowledge contributors before they participate in specific domains.

Data Ownership Marketplace: Ecosystem for trading data ownership rights, enabling monetization of contributions through fractional ownership.

Distribution: In statistics and machine learning, the pattern or function that describes the possible values of a random variable and their associated probabilities, essential for understanding data characteristics and model behavior.

Decentralized Identity (DID): A digital identity system that allows individuals to control their digital identities without relying on a centralized authority.

DID-based Reputation System: Codatta's system for creating persistent professional identities with verifiable credentials and transparent histories.

Domain Adaptation: The process of specializing a general AI model for performance in a specific field (e.g., medicine, law, finance).

Domain Definition: The process of establishing structured data schemas and taxonomies that define parameters for data collection.

Fine-tuning: The process of adapting a pre-trained model to a specific task or domain using additional targeted data.

Foundation Models: Large-scale AI models trained on vast quantities of data that serve as a base for various applications through adaptation or fine-tuning.

Frontier Tokens: Domain-specific tokens that interact with the core XNY system, representing ownership shares in particular data portfolios.

Governance: Decision-making processes in decentralized systems, often implemented through voting mechanisms.

Human Intelligence Protocol: Codatta's decentralized platform for coordinating human knowledge contributions.

Human-in-the-loop: AI systems that incorporate human judgment, feedback, or verification in their operation.

Intelligence: The capacity to acquire and apply knowledge, reason, solve problems, learn from experience, and adapt to new situations. In AI contexts, it refers to a system's ability to perform tasks that would require intelligence if done by humans.

Knowledge Distillation: Transferring knowledge from a large, complex model to a smaller, more efficient model.

Knowledge Layer: The decentralized infrastructure that enables transparent data lineage tracking, flexible compensation, and democratized access to specialized knowledge.

Labeling: The process of assigning categories, tags, or values to data points, creating the ground truth that supervised machine learning models use for training. Similar to annotation but typically refers to simpler classification tasks.

Language Vision Model: AI systems that can process and understand both text and visual information, enabling tasks like image captioning, visual question answering, and text-guided image generation.

Large Language Models (LLMs): AI systems trained on extensive text data that can generate human-like text, understand natural language, and perform various language-related tasks.

Large Model: Machine learning models with billions or trillions of parameters, requiring substantial computational resources for training and inference, but capable of capturing complex patterns across diverse domains.

Machine Learning: A subset of AI focused on building systems that learn from data rather than following explicit programming instructions.

On-chain Contribution Records: Immutable records of data contributions stored on blockchain with metadata including contributor identifiers, timestamps, and usage permissions.

Optimization Algorithm: Mathematical methods used to find the best parameters for a machine learning model by minimizing or maximizing an objective function, typically by iteratively adjusting parameters to reduce prediction errors.

Parameter-Efficient Fine-Tuning: Methods like LoRA (Low-Rank Adaptation) that adapt models by modifying only a small subset of parameters, reducing computational requirements.

Pattern: Regularities or recurring structures in data that machine learning algorithms attempt to identify and learn from. Patterns can be simple correlations or complex relationships across multiple dimensions.

Pre-training: The initial phase of model development where a model learns general patterns from large volumes of data.

Proof-of-Training: Cryptographic proofs that verify and record when specific data is incorporated into AI model training.

Reinforcement Learning from Human Feedback (RLHF): A technique that uses human evaluations to guide model improvement through reinforcement learning.

Reputation-linked Staking: Mechanism where contributors stake tokens to boost their reputation metrics, signaling commitment to quality work.

Royalty-based Reward System: Mechanism for distributing compensation to contributors based on actual usage of their data in AI systems.

Samples: Individual data points or examples used for training, validating, or testing machine learning models. Each sample typically consists of input features and (for supervised learning) corresponding output labels.

Scaling Laws: Principles describing how model performance changes with increases in model size, data volume, and computation.

Smart Contract: Self-executing contracts with terms directly written into code that automatically enforce agreements.

Staking: Locking up cryptocurrency tokens to support network operations and earn rewards.

Supervised Fine-Tuning (SFT): Training a model using labeled examples to improve performance on specific tasks.

Token: Digital assets on a blockchain that can represent value, stake in a platform, or utility within an ecosystem.

Test Data: A separate dataset used to evaluate a trained model's performance on unseen data, providing an unbiased assessment of model generalization.

Training Data: Datasets used to teach machine learning models patterns, relationships, and features by adjusting model parameters to minimize prediction errors.

Trustworthy Evaluation: Codatta's transparent benchmarking system that prevents manipulation through comprehensive transparency mechanisms.

Validation Data: A subset of data separate from training data used during model development to tune hyperparameters and prevent overfitting, providing feedback on model performance before final testing.

XnY Network: Codatta's technical foundation providing a multi-chain abstraction where "X" represents raw data inputs and "Y" represents labels, annotations, or expert opinions.

Web 3.0: The concept of a decentralized internet built on blockchain technology, focusing on user ownership of data, permissionless access, trustless interactions, and distributed applications that operate without central authorities.

X: features: The input variables or attributes in a machine learning system that the model uses to make predictions. Features can be raw data or engineered representations of data characteristics.

XNY Token: Codatta's native utility token used for transaction fees, data access, staking, and governance.

Y: labels: The target outputs or answers that a supervised machine learning model is trained to predict based on input features. Labels represent the "ground truth" that the model aims to learn.

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