Identification Capacity and Rate-Query Tradeoffs in Classification Systems

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***Abstract*—We extend classical rate-distortion and zero-error identification to a discrete classification setting with three resources: *tag rate* L (bits of storage per entity), *identification cost* W (attribute queries to determine class membership), and *distortion* D (misidentification probability). The central question is how these resources trade off when an observer must identify class identity from constrained evidence.**

Information barrier (zero-error identifiability). When distinct classes share identical attribute profiles, no algorithm, regardless of computational power, can identify class identity from attribute queries alone. Formally: if π is not injective on classes, then zero-error identification from attribute queries alone is impossible.

Rate-identification tradeoff. Let $A_\pi := \max_u |\{c : \pi(c) = u\}|$ be the maximum collision multiplicity induced by the attribute profile map. We show that zero-error identification requires at least $\lceil \log_2 A_\pi \rceil$ tag bits, and this bound is tight. In the maximal-barrier regime ($A_\pi = k$), the nominal-tag point $(L, W, D) = (\lceil \log_2 k \rceil, O(1), 0)$ is the unique Pareto-optimal zero-error point. Without tags ($L = 0$), zero-error identification requires $W = \Omega(d)$ attribute queries, where d is the distinguishing dimension; in the worst case $d = n$ (the ambient attribute count), giving $W = \Omega(n)$.

Converse. For any domain, any scheme achieving $D = 0$ requires $L \geq \log_2 A_\pi$ bits. As a corollary, in maximal-barrier domains ($A_\pi = k$), any zero-error scheme requires $L \geq \log_2 k$ bits. Nominal tagging achieves these bounds with $W = O(1)$.

Matroid structure. Minimal sufficient query sets form the bases of a matroid. The *distinguishing dimension* (the common cardinality of all minimal query sets) is well-defined, connecting to zero-error source coding via graph entropy.

Cross-domain corollary. The theory instantiates to databases (key vs. attribute lookup), knowledge graphs, biological taxonomy (genotype vs. phenotype), and typed software systems (nominal vs. structural classification). The unbounded gap $\Omega(d)$ vs. $O(1)$ (with a worst-case family where $d = n$) gives a formal cost account for when nominal identity metadata becomes necessary rather than stylistic. As a modern corollary, the same ambiguity converse applies to model-identity metadata in learning systems: zero-error identification requires at least $\lceil \log_2 A_\pi \rceil$ bits, while attribute-only identification can require $\Omega(d)$ feature queries.

All results are machine-checked in Lean 4 (6589 lines, 296 theorem/lemma statements, 0 `sorry`).

Keywords: rate-distortion theory, identification capacity, zero-error source coding, query complexity, matroid structure, classification systems

I. Introduction

A. The Identification Problem

Consider an encoder-decoder pair communicating about entities from a large universe $\mathcal{V}$. The decoder must *identify* each entity, determining which of k classes it belongs to, using only:

- A *tag* of L bits stored with the entity, and/or
- *Queries* to a binary oracle: "does entity v satisfy attribute I?"

This is not reconstruction (the decoder need not recover v), but *identification* in the sense of Ahlswede and Dueck [1]: the decoder must answer "which class?" with zero or bounded error. Our work extends this framework to consider the tradeoff between tag storage, query complexity, and identification accuracy.

We prove three results:

1) **Information barrier (identifiability limit).** When the attribute profile $\pi : \mathcal{V} \to \{0,1\}^n$ is not injective on classes, zero-error identification via queries alone is impossible: any decoder produces identical output on colliding classes, so cannot be correct for both.
2) **Optimal tagging (achievability).** A tag of $L = \lceil \log_2 k \rceil$ bits achieves zero-error identification with $W = O(1)$ query cost. For maximal-barrier domains ($A_\pi = k$), this is the unique Pareto-optimal point in the (L, W, D) tradeoff space at $D = 0$; in general domains, the converse depends on $A_\pi := \max_u |\{c : \pi(c) = u\}|$.
3) **Matroid structure (query complexity).** Minimal sufficient query sets form the bases of a matroid. The *distinguishing dimension* (the common cardinality of all minimal sets) is well-defined and lower-bounds the query cost W for any tag-free scheme.

These results are universal: the theory applies to type systems, databases, biological taxonomy, and knowledge graphs. We develop the mathematics in full generality, then exhibit concrete instantiations.

B. The Observation Model

We formalize the observational constraint as a family of binary predicates. The terminology is deliberately abstract; concrete instantiations follow in Section VII.

Definition I.1 (Entity space and attribute family)**.** Let $\mathcal{V}$ be a set of entities (program objects, database records, biological specimens, library items). Let $\mathcal{I}$ be a finite set of binary *attributes*. Each $I \in \mathcal{I}$ induces a bipartition of $\mathcal{V}$ via q_I, and the full family induces the observational equivalence partition.

Remark I.2 (Terminology)*.* We use "attribute" for the abstract concept. In type systems, attributes are *interfaces* or *method signatures*. In databases, they are *columns*. In taxonomy, they are *phenotypic characters*. In library science, they are *facets*. The mathematics is identical.

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Definition I.3 (Attribute observation family)**.** For each $I \in \mathcal{I}$, define the attribute-membership observation $q_I : \mathcal{V} \to \{0,1\}$:

$$q_I(v) = \begin{cases} 1 & \text{if } v \text{ satisfies attribute } I \\ 0 & \text{otherwise} \end{cases}$$

Let $\Phi_{\mathcal{I}} = \{q_I : I \in \mathcal{I}\}$ denote the attribute observation family.

Remark I.4 (Notation for size parameters). We write $n := |\mathcal{I}|$ for the ambient number of available attributes. We write d for the distinguishing dimension (the common size of all minimal distinguishing query sets; Definition IV.9), so $d \leq n$ and there exist worst-case families with $d = n$. We write m for the number of *query sites* (call sites) that perform attribute checks in a program or protocol (used only in the complexity-of-maintenance discussion). When discussing a particular identification/verification task, we may write s for the number of attributes actually queried/traversed by the procedure (e.g., members/fields checked in a structural type test, phenotypic characters checked in taxonomy), with $s \leq n$. The maintenance-only parameter m appears only in Section III.

Definition I.5 (Attribute profile)**.** The attribute profile function $\pi : \mathcal{V} \to \{0,1\}^{|\mathcal{I}|}$ maps each value to its complete attribute signature:

$$\pi(v) = (q_I(v))_{I \in \mathcal{I}}$$

Definition I.6 (Attribute indistinguishability)**.** Values $v, w \in \mathcal{V}$ are *attribute-indistinguishable*, written $v \sim w$, iff $\pi(v) = \pi(w)$.

The relation $\sim$ is an equivalence relation. We write $[v]_\sim$ for the equivalence class of v.

Definition I.7 (Attribute-only observer)**.** An *attribute-only observer* is any procedure whose interaction with a value $v \in \mathcal{V}$ is limited to queries in $\Phi_{\mathcal{I}}$. Formally, the observer interacts with v only via primitive attribute queries $q_I \in \Phi_{\mathcal{I}}$; hence any transcript (and output) factors through $\pi(v)$.

C. The Central Question

The central question is: **what semantic properties can an attribute-only observer compute?**

A semantic property is a function $P : \mathcal{V} \to \{0,1\}$ (or more generally, $P : \mathcal{V} \to Y$ for some codomain Y). We say P is *attribute-computable* if there exists a function $f : \{0,1\}^{|\mathcal{I}|} \to Y$ such that $P(v) = f(\pi(v))$ for all v.

D. The Information Barrier

Theorem I.8 (Information barrier)**.** *Let $P : \mathcal{V} \to Y$ be any function. If P is attribute-computable, then P is constant on $\sim$-equivalence classes:*

$$v \sim w \implies P(v) = P(w)$$

Equivalently: no attribute-only observer can compute any property that varies within an equivalence class.

Proof. Suppose P is attribute-computable via f, i.e., $P(v) = f(\pi(v))$ for all v. Let $v \sim w$, so $\pi(v) = \pi(w)$. Then:

$$P(v) = f(\pi(v)) = f(\pi(w)) = P(w)$$

■

Remark I.9 (Information-theoretic nature). The barrier is *informational*, not computational. Given unlimited time, memory, and computational power, an attribute-only observer still cannot distinguish v from w when $\pi(v) = \pi(w)$. The constraint is on the evidence itself.

Remark I.10 (Role in the paper). Theorem I.8 is the foundational invariance statement. The technical contribution is the downstream structure built on top of it: the ambiguity-based converse (Theorem II.30), the Pareto characterization (Theorem VI.3), and the matroid/equicardinality results (Section IV).

Corollary I.11 (Class identity is not attribute-computable)**.** *Let $C : \mathcal{V} \to \{1, \ldots, k\}$ be the class assignment function. If there exist values v, w with $\pi(v) = \pi(w)$ but $C(v) \neq C(w)$, then class identity is not attribute-computable.*

Proof. Direct application of Theorem I.8 to $P = C$. ■

E. The Positive Result: Nominal Tagging

We now show that augmenting attribute observations with a single primitive, nominal-tag access, achieves constant witness cost.

Definition I.12 (Nominal-tag access)**.** A *nominal tag* is a value $\tau(v) \in \mathcal{T}$ associated with each $v \in \mathcal{V}$, representing the class identity of v. The *nominal-tag access* operation returns $\tau(v)$ in $O(1)$ time.

Definition I.13 (Primitive query set)**.** The extended primitive query set is $\Phi^+_{\mathcal{I}} = \Phi_{\mathcal{I}} \cup \{\tau\}$, where τ denotes nominal-tag access.

Definition I.14 (Witness cost)**.** Let $W(P)$ denote the minimum number of primitive queries from $\Phi^+_{\mathcal{I}}$ required to compute property P. We distinguish two tasks:

- W_{id}: Cost to identify the class of a single entity.
- W_{eq}: Cost to determine if two entities have the same class.

Unless specified, W refers to W_{eq}.

Theorem I.15 (Constant witness for class identity)**.** *Under nominal-tag access, class identity checking has constant witness cost:*

$$W(\textit{class-identity}) = O(1)$$

Specifically, the witness procedure is: return $\tau(v_1) = \tau(v_2)$.

Proof. The procedure makes exactly 2 primitive queries (one τ access per value) and one comparison. This is $O(1)$ regardless of the number of available attributes $|\mathcal{I}|$. ■

Theorem I.16 (Attribute-only lower bound)**.** *For attribute-only observers, class identity checking requires:*

$$W(\textit{class-identity}) = \Omega(d)$$

in the worst case, where d is the distinguishing dimension (Definition IV.9).

Proof. Assume a zero-error attribute-only procedure halts after fewer than d queries on every execution path. Fix any execution path and let $Q \subseteq \mathcal{I}$ be the set of queried attributes on that path, so $|Q| < d$. Since d is the cardinality of every minimal distinguishing set, no set of size $< d$ is distinguishing; hence there exist values v, w from different classes with identical answers on all attributes in Q.

An adversary can answer the procedure's queries consistently with both v and w along this path. Therefore the resulting transcript (and output) is identical on v and w, contradicting zero-error class identification. So some execution path must use at least d queries, giving worst-case cost $\Omega(d)$. ■

F. Main Contributions

This paper establishes the following results:

1) **Information Barrier Theorem** (Theorem I.8): Attribute-only observers cannot compute any property that varies within $\sim$-equivalence classes. This is an information-theoretic impossibility, not a computational limitation.
2) **Constant-Witness Theorem** (Theorem I.15): Nominal-tag access achieves $W(\text{class-identity}) = O(1)$, with matching lower bound $\Omega(d)$ for attribute-only observers (Theorem I.16), where d is the distinguishing dimension (Definition IV.9).
3) **Complexity Separation** (Section III): We establish O(1) vs O(k) vs $\Omega(d)$ complexity bounds for error localization under different observation regimes (where d is the distinguishing dimension).
4) **Matroid Structure** (Section IV): Minimal distinguishing query sets form the bases of a matroid. All such sets have equal cardinality, establishing a well-defined "distinguishing dimension."
5) (L, W, D) **Optimality** (Section VI): We characterize the zero-error converse via collision multiplicity A_π and prove uniqueness of the nominal point in the maximal-barrier regime ($A_\pi = k$).
6) **Machine-Checked Proofs**: All results formalized in Lean 4 (6589 lines, 296 theorem/lemma statements, 0 `sorry` placeholders).

G. Related Work and Positioning

Identification via channels. Our work extends the identification paradigm introduced by Ahlswede and Dueck [1], [2]. In their framework, a decoder need not reconstruct a message but only answer "is the message m?" for a given hypothesis. This yields dramatically different capacity: double-exponential codebook sizes become achievable. Our setting differs in three ways: (1) we consider zero-error identification rather than vanishing error, (2) queries are adaptive rather than block codes, and (3) we allow auxiliary tagging (rate L) to reduce query cost. The (L, W, D) tradeoff generalizes Ahlswede-Dueck to a multi-dimensional operating regime.

Rate-distortion theory. The (L, W, D) framework connects to Shannon's rate-distortion theory [3], [4] with an important twist: the "distortion" D is semantic (class misidentification), and there is a second resource W (query cost) alongside rate L. Classical rate-distortion asks: what is the minimum rate to achieve distortion D? We ask: given rate L, what is the minimum query cost W to achieve distortion $D = 0$? Theorem VI.3 gives the converse in terms of collision multiplicity and identifies the unique nominal point in the maximal-barrier regime.

Rate-distortion-perception tradeoffs. Blau and Michaeli [5] extended rate-distortion theory by adding a perception constraint, creating a three-way tradeoff. Our query cost W plays an analogous role: it measures the interactive cost of achieving low distortion rather than a distributional constraint. This parallel suggests that (L, W, D) tradeoffs may admit similar geometric characterizations. Section VIII develops this connection further.

Zero-error information theory. The matroid structure (Section IV) connects to zero-error capacity and graph entropy. Körner [6] and Witsenhausen [7] studied zero-error source coding where confusable symbols must be distinguished. Our distinguishing dimension (Definition IV.9) is the minimum number of binary queries to separate all classes, which is precisely the zero-error identification cost when $L = 0$.

Query complexity and communication complexity. The $\Omega(d)$ lower bound for attribute-only identification relates to decision tree complexity [8] and interactive communication [9]. The key distinction is that our queries are constrained to a fixed observable family $\mathcal{I}$, not arbitrary predicates.

Compression in classification systems. The framework applies uniformly to databases, knowledge graphs, taxonomy, and typed software systems: for zero-error identification, ambiguity induces a minimum metadata requirement $L \geq \log_2 A_\pi$ (Theorem II.30), with maximal-barrier specialization $L \geq \log_2 k$.

Programming-language corollary (secondary). In nominal-vs-structural typing settings [10], [11], the model yields a concrete cost statement: under attribute collisions, purely structural identification has worst-case $\Omega(d)$ witness cost, while nominal tags achieve $O(1)$ identification using $O(\log A_\pi)$ bits. This is the paper's PL-facing corollary; the main contribution remains the information-theoretic characterization.

H. Paper Organization

Section II formalizes the compression framework and defines the (L, W, D) tradeoff. Section III establishes complexity bounds for error localization. Section IV proves the matroid structure of distinguishing query families. Section V analyzes witness cost in detail. Section VI proves the ambiguity-based converse and Pareto characterization. Section VII provides cross-domain instantiations as secondary illustrations. Section IX concludes. Appendix A describes the Lean 4 formalization.

II. Compression Framework

A. Semantic Compression: The Problem

The fundamental problem of *semantic compression* is: given a value v from a large space $\mathcal{V}$, how can we represent v compactly while preserving the ability to answer semantic queries about v? This differs from classical source coding in that the goal is not reconstruction but *identification*: determining which equivalence class v belongs to.

Classical rate-distortion theory [3] studies the tradeoff between representation size and reconstruction fidelity. We extend this to a discrete classification setting with three dimensions: *tag length* L (bits of storage), *witness cost* W (queries or bits of communication required to determine class membership), and *distortion* D (misclassification probability).

This work exemplifies the convergence of classical information theory with modern data systems: we extend Shannon's rate-distortion framework to contemporary classification problems (databases, knowledge graphs, ML model registries), proving fundamental limits that were implicit in practice but not formalized in classical theory.

B. Universe of Discourse

Definition II.1 (Classification scheme)**.** A *classification scheme* is any procedure (deterministic or randomized), with arbitrary time and memory, whose only access to a value $v \in \mathcal{V}$ is via:

1) The *observation family* $\Phi = \{q_I : I \in \mathcal{I}\}$, where $q_I(v) = 1$ iff v satisfies attribute I; and optionally
2) A *nominal-tag primitive* $\tau : \mathcal{V} \to \mathcal{T}$ returning an opaque class identifier.

All theorems in this paper quantify over all such schemes.

This definition is intentionally broad: schemes may be adaptive, randomized, or computationally unbounded. The constraint is *observational*, not computational.

Theorem II.2 (Information barrier)**.** *For all classification schemes with access only to Φ (no nominal tag), the output is constant on $\sim_\Phi$-equivalence classes. Therefore, no such scheme can compute any property that varies within a $\sim_\Phi$-class.*

Proof. Let $v \sim_\Phi w$, meaning $q_I(v) = q_I(w)$ for all $I \in \mathcal{I}$. Any scheme's execution trace depends only on query responses. Since all queries return identical values for v and w, the scheme cannot distinguish them. Any output must therefore be identical. ∎

Proposition II.3 (Model capture)**.** *Any real-world classification protocol whose evidence consists solely of attribute-membership queries is representable as a scheme in the above model. Conversely, any additional capability corresponds to adding new observations to Φ.*

This proposition forces any objection into a precise form: to claim the theorem does not apply, one must name the additional observation capability not in Φ. "Different universe" is not a coherent objection; it must reduce to "I have access to oracle $X \notin \Phi$."

C. Two-Axis Instantiation (Programming Languages)

The core information-theoretic results of this paper require only $(\mathcal{V}, C, \pi)$ and the observation family Φ. The two-axis decomposition below is an explicit programming-language instantiation used in Sections VII and A, not an additional axiom for the general theorems.

In that instantiation, each value is characterized by:

- **Lineage axis** (B): The provenance chain of the value's class (which classes it derives from, in what order)[1]
- **Profile axis** (S): The observable attribute profile (interfaces/method signatures in the PL instantiation)

Definition II.4 (Two-axis representation)**.** A value $v \in \mathcal{V}$ has representation $(B(v), S(v))$ where:

$$B(v) = \text{lineage}(\text{class}(v)) \quad \text{(class derivation chain)} \qquad (1)$$

$$S(v) = \pi(v) = (q_I(v))_{I \in \mathcal{I}} \quad \text{(attribute profile)} \qquad (2)$$

The lineage axis captures *nominal* identity: where the class comes from. The profile axis captures *structural* identity: what the value can do.

In the PL instantiation, B is carried by the runtime lineage order (e.g., C3/MRO output). Any implementation-specific normalization or lookup machinery is auxiliary and does not define inheritance (Appendix A).

Theorem II.5 (Fixed-axis completeness)**.** *Let a fixed-axis domain be specified by an axis map $\alpha : \mathcal{V} \to \mathcal{A}$ and an observation family Φ such that each primitive query $q \in \Phi$ factors through α. Then every in-scope semantic property (i.e., any property computable by an admissible Φ-only strategy) factors through α: there exists $\tilde{P}$ with*

$$P(v) = \tilde{P}(\alpha(v)) \quad \textit{for all } v \in \mathcal{V}.$$

In the PL instantiation, $\alpha(v) = (B(v), S(v))$, so in-scope semantic properties are functions of (B, S).

Proof. An admissible Φ-only strategy observes v solely through responses to primitive queries $q_I \in \Phi$. By hypothesis each such response is a function of $\alpha(v)$. Therefore every query transcript, and hence any strategy's output, depends only on $\alpha(v)$, so the computed property factors through α. ∎

Corollary II.6 (Fixed-Axis Incompleteness)**.** *Any fixed-axis classification system is complete only for properties measurable on the fixed axis map α, and incomplete for any property that varies within an α-fiber. Equivalently, if $\alpha(v) = \alpha(w)$ but $P(v) \neq P(w)$, then no admissible Φ-only strategy can compute P with zero error.*

D. Attribute Equivalence and Observational Limits

Recall from Section 1 the attribute equivalence relation:

Definition II.7 (Attribute equivalence (restated))**.** Values $v, w \in \mathcal{V}$ are attribute-equivalent, written $v \sim w$, iff $\pi(v) = \pi(w)$, i.e., they induce exactly the same attribute responses.

Proposition II.8 (Equivalence class structure)**.** *The relation $\sim$ partitions $\mathcal{V}$ into equivalence classes. Let $\mathcal{V}/\sim$ denote the quotient space. An attribute-only observer effectively operates on $\mathcal{V}/\sim$, not $\mathcal{V}$.*

[1] In the Lean formalization (Appendix A), the lineage axis is denoted `Bases`, reflecting its instantiation as the inheritance chain in object-oriented languages.

Corollary II.9 (Information loss quantification)**.** *The information lost by attribute-only observation is:*

$$H(\mathcal{V}) - H(\mathcal{V}/\sim) = H(\mathcal{V}|\pi)$$

where H denotes entropy. This quantity is positive whenever multiple classes share the same attribute profile.

E. Identification Capacity

We now formalize the identification problem in channel-theoretic terms. Let $C : \mathcal{V} \to \{1, \dots, k\}$ denote the class assignment function, and let $\pi : \mathcal{V} \to \{0, 1\}^n$ denote the attribute profile.

Definition II.10 (Identification channel)**.** The *identification channel* induced by observation family Φ is the mapping $C \to \pi(V)$ for a random entity V drawn from distribution P_V over $\mathcal{V}$. The channel output is the attribute profile; the channel input is implicitly the class $C(V)$.

Theorem II.11 (Zero-Error Identification Feasibility (One Shot))**.** *Let $\mathcal{C} = \{1, \dots, k\}$ be the class space. The* zero-error identification capacity *of the observation channel is:*

$$C_{id} = \begin{cases} \log_2 k & \text{if } \pi \text{ is injective on classes} \\ 0 & \text{otherwise} \end{cases}$$

That is, zero-error identification of all k classes is achievable if and only if every class has a distinct attribute profile. When π is not class-injective, no rate of identification is achievable with zero error.

Proof. Achievability: If π is injective on classes, then observing $\pi(v)$ determines $C(v)$ uniquely. The decoder simply inverts the class-to-profile mapping.

Converse (deterministic): Suppose two distinct classes $c_1 \neq c_2$ share a profile: $\exists v_1 \in c_1, v_2 \in c_2$ with $\pi(v_1) = \pi(v_2)$. Then any decoder $g(\pi(v))$ outputs the same class label on both v_1 and v_2, so it cannot be correct for both. Hence zero-error identification of all classes is impossible. ∎

Remark II.12 (Information-theoretic corollary). Under any distribution with positive mass on both colliding classes, $I(C; \pi(V)) < H(C)$. This is an average-case consequence of the deterministic barrier above.

Remark II.13 (Relation to Ahlswede-Dueck). In the identification paradigm of [1], the decoder asks "is the message m?" rather than "what is the message?" This yields double-exponential codebook sizes. Our setting is different: we require zero-error identification of the *class*, not hypothesis testing. The one-shot zero-error identification feasibility threshold (π must be class-injective) is binary rather than a rate.

Remark II.14 (Terminology). Theorem II.11 is a one-shot feasibility statement, not a Shannon asymptotic coding theorem. We retain C_{id} notation only to align with identification-theory language.

The key insight is that tagging provides a *side channel* that restores identifiability when the attribute channel fails:

Theorem II.15 (Tag-Restored Zero Error (Sufficiency))**.** *A class-injective nominal tag of length $L \geq \lceil \log_2 k \rceil$ bits suffices for zero-error identification, regardless of whether π is class-injective.*

Proof. A nominal tag $\tau : \mathcal{V} \to \{1, \dots, k\}$ assigns a unique identifier to each class. Reading $\tau(v)$ determines $C(v)$ in $O(1)$ queries, independent of the attribute channel. ∎

F. Witness Cost: Query Complexity for Semantic Properties

Definition II.16 (Witness procedure)**.** A *witness procedure* for property $P : \mathcal{V} \to Y$ is an algorithm A that:

1) Takes as input a value $v \in \mathcal{V}$ (via query access only)
2) Makes queries to the primitive set $\Phi^+_{\mathcal{I}}$
3) Outputs $P(v)$

Definition II.17 (Witness cost)**.** The *witness cost* of property P is:

$$W(P) = \min_{A \text{ computes } P} c(A)$$

where $c(A)$ is the worst-case number of primitive queries made by A.

Remark II.18 (Relationship to query complexity). Witness cost is a form of query complexity [8] specialized to semantic properties. Unlike Kolmogorov complexity, W is computable and depends on the primitive set, not a universal machine.

Lemma II.19 (Witness cost lower bounds)**.** *For any property P:*

1) *If P is attribute-computable: $W(P) \leq |\mathcal{I}|$*
2) *If P varies within some $\sim$-class: $W(P) = \infty$ for attribute-only observers*
3) *With nominal-tag access: $W(\text{class-identity}) = O(1)$*

G. The (L, W, D) Tradeoff

We now define the three-dimensional tradeoff space that characterizes observation strategies, using information-theoretic units.

Definition II.20 (Tag rate)**.** For a set of class identifiers (tags) $\mathcal{T}$ with $|\mathcal{T}| = k$, the *tag rate* L is the minimum number of bits required to encode a class identifier:

$$L \geq \log_2 k \quad \text{bits per value}$$

For nominal-tag observers, $L = \lceil \log_2 k \rceil$ (optimal prefix-free encoding). For attribute-only observers, $L = 0$ (no explicit tag stored). Under a distribution P over classes, the expected tag length is $\mathbb{E}[L] \geq H(P)$ by Shannon's source coding theorem [3].

Definition II.21 (Witness cost (Query/Communication complexity))**.** The *witness cost* W is the minimum number of primitive queries (or bits of interactive communication) required for class identification:

$$W = \min_{A \text{ decides class}} c(A)$$

where $c(A)$ is the worst-case query count. This is a form of query complexity [8] or interactive identification cost.

Definition II.22 (Class estimator)**.** Fix class map $C : \mathcal{V} \to \{1, \ldots, k\}$. An observation strategy g induces an estimate

$$\hat{C}_g(v; \omega) \in \{1, \ldots, k\}$$

from the available evidence (tag bits, query transcript, and optional internal randomness ω).

Definition II.23 (Distortion indicator and expected distortion)**.** For strategy g, define

$$d_g(v; \omega) := \mathbf{1}\left[\hat{C}_g(v; \omega) \neq C(v)\right].$$

Under data distribution P_V and strategy randomness, expected distortion is

$$D(g) = \Pr_{v \sim P_V, \omega}\left[\hat{C}_g(v; \omega) \neq C(v)\right].$$

The zero-error regime is $D(g) = 0$.

Remark II.24 (Interpretation). In this paper, D is strictly class-misidentification probability. Additional semantic notions (e.g., hierarchical or behavior-weighted penalties) are treated as extensions in Section VIII.

H. The (L, W, D) Tradeoff Space

Admissible schemes. To make the Pareto-optimality claim precise, we specify the class of admissible observation strategies:

- **Deterministic or randomized**: Schemes may use randomness; W is worst-case query count.
- **Computationally unbounded**: No time/space restrictions; the constraint is observational.
- **No preprocessing over class universe**: The scheme cannot precompute a global lookup table indexed by all possible classes.
- **Tags are injective on classes**: A nominal tag $\tau(v)$ uniquely identifies the class of v. Variable-length or compressed tags are permitted; L counts bits.
- **No amortization across queries**: W is per-identification cost, not amortized over a sequence.

Justification. The "no preprocessing" and "no amortization" constraints exclude trivializations:

- *Preprocessing*: With unbounded preprocessing over the class universe $\mathcal{T}$, one could build a lookup table mapping attribute profiles to classes. This reduces identification to $O(1)$ table lookup, but the table has size $O(|\mathcal{T}|)$, hiding the complexity in space rather than eliminating it. The constraint models systems that cannot afford $O(|\mathcal{T}|)$ storage per observer.
- *Amortization*: If W were amortized over a sequence of identifications, one could cache earlier results. This again hides complexity in state. The per-identification model captures stateless observers (typical in database queries, taxonomy lookup, and protocol/classification services).

Dropping these constraints changes the achievable region but not the qualitative separation: nominal tags still dominate for $D = 0$ because they provide $O(1)$ worst-case identification without requiring $O(|\mathcal{T}|)$ preprocessing.

Under these rules, "dominance" means strict improvement on at least one of (L, W, D) with no regression on others.

Definition II.25 (Achievable region)**.** A point (L, W, D) is *achievable* if there exists an admissible observation strategy realizing those values. Let $\mathcal{R} \subseteq \mathbb{R}_{\geq 0} \times \mathbb{R}_{\geq 0} \times [0, 1]$ denote the achievable region.

Definition II.26 (Pareto optimality)**.** A point (L^*, W^*, D^*) is *Pareto-optimal* if there is no achievable (L, W, D) with $L \leq L^*$, $W \leq W^*$, $D \leq D^*$, and at least one strict inequality.

The main result of Section VI is: (i) a converse in terms of collision multiplicity A_π, and (ii) uniqueness of the nominal $D = 0$ Pareto point in the maximal-barrier regime.

Definition II.27 (Information-barrier domain)**.** A classification domain has an *information barrier* (relative to Φ) if there exist distinct classes $c_1 \neq c_2$ with identical Φ-profiles. Equivalently, π is not injective on classes.

Definition II.28 (Collision multiplicity)**.** Let $\mathcal{C} = \{1, \ldots, k\}$ and let $\pi_{\mathcal{C}} : \mathcal{C} \to \{0, 1\}^n$ be the class-level profile map. Define

$$A_\pi := \max_{u \in \mathrm{Im}(\pi_{\mathcal{C}})} |\{c \in \mathcal{C} : \pi_{\mathcal{C}}(c) = u\}|.$$

Thus A_π is the size of the largest class-collision block under observable profiles.

Definition II.29 (Maximal-Barrier Regime)**.** The domain is *maximal-barrier* if $A_\pi = k$, i.e., all classes collide under the observation map.

I. Converse: Tag Rate Lower Bound

Theorem II.30 (Converse)**.** *For any classification domain, any scheme achieving $D = 0$ requires*

$$2^L \geq A_\pi \quad \textit{equivalently} \quad L \geq \log_2 A_\pi,$$

where A_π is the collision multiplicity from Definition II.28.

Proof. Fix a collision block $G \subseteq \mathcal{C}$ with $|G| = A_\pi$ and identical observable profile. For classes in G, query transcripts are identical, so zero-error decoding must separate those classes using tag outcomes. With L tag bits there are at most 2^L outcomes, hence $2^L \geq |G| = A_\pi$. ■

Corollary II.31 (Maximal-Barrier Converse)**.** *If the domain is maximal-barrier ($A_\pi = k$), any zero-error scheme satisfies $L \geq \log_2 k$.*

J. Lossy Regime: Deterministic vs Noisy Models

The zero-error corner ($D = 0$) is governed by Theorem II.30. For $D > 0$, the model matters:

- **Deterministic queries (this section):** there is no universal law of the form $W = O(\log(1/\epsilon) \cdot d)$. If classes collide on all deterministic observations, repeating those same observations does not reduce error.
- **Noisy queries (Section VIII):** repeated independent observations can reduce error exponentially, yielding logarithmic-in-$1/\epsilon$ sample complexity.

Thus, in the deterministic model, distortion is controlled by collision geometry and decision rules; in noisy models, repetition-based concentration bounds become relevant.

TABLE I
IDENTIFICATION STRATEGIES FOR 1000 CLASSES WITH 50 ATTRIBUTES.

Strategy	**Tag** L	**Witness** W
Nominal (class ID)	$\lceil \log_2 1000 \rceil = 10$ bits	$O(1)$
Duck typing (query all)	0	≤ 50 queries
Adaptive duck typing	0	$\geq d$ queries

K. Concrete Example

Consider a classification system with $k = 1000$ classes, each characterized by a subset of $n = 50$ binary attributes. Table I compares the strategies.

Here d is the distinguishing dimension, the size of any minimal distinguishing query set. For typical hierarchies, $d \approx 5$–15. The gap between 10 bits of storage vs. 5–50 queries per identification is the cost of forgoing nominal tagging.

III. Complexity Bounds

A. The Error Localization Theorem

a) Scope of this section.: This section studies *maintenance/localization* complexity, measured by locations to inspect ($E(\cdot)$), not per-instance identification complexity (W) from Sections II and V. The metrics are related but distinct: W quantifies online class-identification effort, while E quantifies where constraint logic is distributed in implementations.

Definition III.1 (Error location count)**.** Let $E(\mathcal{O})$ be the number of locations that must be inspected to find all potential violations of a constraint under observation family $\mathcal{O}$.

Theorem III.2 (Nominal-tag localization)**.** *$E(\textit{nominal-tag}) = O(1)$.*

Proof. Under nominal-tag observation, the constraint "v must be of class A" is satisfied iff $\tau(v) \in \text{subtypes}(A)$. This is determined at a single location: the definition of $\tau(v)$'s class. One location. ∎

Theorem III.3 (Declared-attribute localization)**.** *$E(\textit{attribute-only, declared}) = O(k)$ where k = number of entity classes.*

Proof. With declared attribute sets (interfaces in the PL instantiation), the constraint "v must satisfy attribute I" requires verifying that each class satisfies all attributes in I. For k classes, $O(k)$ locations. ∎

Theorem III.4 (Attribute-only localization)**.** *$E(\textit{attribute-only}) = \Omega(m)$ where m = number of query sites.*

Proof. Under attribute-only observation, each query site independently checks "does v have attribute a?" with no centralized declaration. For m query sites, each must be inspected. Lower bound is $\Omega(m)$. ∎

Corollary III.5 (Strict dominance)**.** *Nominal-tag observation strictly dominates attribute-only: $E(\textit{nominal-tag}) = O(1) < \Omega(m) = E(\textit{attribute-only})$ for all $m > 1$.*

B. The Information Scattering Theorem

Definition III.6 (Constraint encoding locations)**.** Let $I(\mathcal{O}, c)$ be the set of locations where constraint c is encoded under observation family $\mathcal{O}$.

Theorem III.7 (Attribute-only scattering)**.** *For attribute-only observation, $|I(\textit{attribute-only}, c)| = O(m)$ where m = query sites using constraint c.*

Proof. Each attribute query independently encodes the constraint. No shared reference exists. Constraint encodings scale with query sites. ∎

Theorem III.8 (Nominal-tag centralization)**.** *For nominal-tag observation, $|I(\textit{nominal-tag}, c)| = O(1)$.*

Proof. The constraint "must be of class A" is encoded once in the definition of A. All tag checks reference this single definition. ∎

Corollary III.9 (Maintenance entropy)**.** *Attribute-only observation maximizes maintenance entropy; nominal-tag observation minimizes it.*

IV. Matroid Structure

A. Model Contract (Fixed-Axis Domains)

Model contract (fixed-axis domain). A domain is specified by a fixed observation family Φ derived from a fixed axis map $\alpha : \mathcal{V} \to \mathcal{A}$ (e.g., $\alpha(v) = (B(v), S(v))$). An observer is permitted to interact with v only through primitive queries in Φ, and each primitive query factors through α: for every $q \in \Phi$, there exists $\tilde{q}$ such that $q(v) = \tilde{q}(\alpha(v))$. A property is in-scope semantic iff it is computable by an admissible strategy that uses only responses to queries in Φ (under our admissibility constraints: no global preprocessing tables, no amortized caching, etc.).

We adopt Φ as the complete observation universe for this paper: to claim applicability to a concrete runtime one must either (i) exhibit mappings from each runtime observable into Φ, or (ii) enforce the admissibility constraints (no external registries, no reflection, no preprocessing/amortization). Under either condition the theorems apply without qualification.

Proposition IV.1 (Observational Quotient)**.** *For any admissible strategy using only Φ, the entire interaction transcript (and hence the output) depends only on $\alpha(v)$. Equivalently, any in-scope semantic property P factors through α: there exists $\tilde{P}$ with $P(v) = \tilde{P}(\alpha(v))$ for all v.*

Corollary IV.2 (Why "ad hoc" = adding an axis/tag)**.** *If two values v, w satisfy $\alpha(v) = \alpha(w)$, then no admissible Φ-only strategy can distinguish them with zero error. Any mechanism that does distinguish such pairs must introduce additional information not present in α (equivalently, refine the axis map by adding a new axis/tag).*

B. Query Families and Distinguishing Sets

The classification problem is: given a set of queries, which subsets suffice to distinguish all entities?

Definition IV.3 (Query family)**.** Let $\mathcal{Q}$ be the set of all primitive queries available to an observer. For a classification system with attribute set $\mathcal{I}$, we have $\mathcal{Q} = \{q_I : I \in \mathcal{I}\}$ where $q_I(v) = 1$ iff v satisfies attribute I.

In this section, "queries" are the primitive attribute predicates $q \in \Phi$ (equivalently, each q factors through the axis map: $q = \tilde{q} \circ \alpha$). See the Convention above where $\Phi := \mathcal{Q}$.
Convention: $\Phi := \mathcal{Q}$. All universal quantification over "queries" ranges over $q \in \Phi$ only.

Definition IV.4 (Distinguishing set)**.** A subset $S \subseteq \mathcal{Q}$ is *distinguishing* if, for all values v, w with $\text{class}(v) \neq \text{class}(w)$, there exists $q \in S$ such that $q(v) \neq q(w)$.

Definition IV.5 (Minimal distinguishing set)**.** A distinguishing set S is *minimal* if no proper subset of S is distinguishing.

C. Matroid Structure of Query Families

Scope and assumptions. The matroid theorem below is unconditional within the fixed-axis observational theory defined above. In this section, "query" always means a primitive predicate $q \in \Phi$ (equivalently, q factors through α as in the Model Contract). It depends only on:

- $E = \Phi$ is the ground set of primitive queries (attribute predicates).
- "Distinguishing": for all values v, w with $\text{class}(v) \neq \text{class}(w)$, there exists $q \in S$ such that $q(v) \neq q(w)$ (Def. above).
- "Minimal" means inclusion-minimal: no proper subset suffices.

No further assumptions are required within this theory (i.e., beyond the fixed observation family Φ already specified). The proof constructs a closure operator satisfying extensivity, monotonicity, and idempotence, from which basis exchange follows (see Lean formalization).

Definition IV.6 (Bases family)**.** Let $E = \Phi$ $(= \mathcal{Q})$ be the ground set of primitive queries (attribute predicates). Let $\mathcal{B} \subseteq 2^E$ be the family of minimal distinguishing sets.

Lemma IV.7 (Basis exchange)**.** *For any $B_1, B_2 \in \mathcal{B}$ and any $q \in B_1 \setminus B_2$, there exists $q' \in B_2 \setminus B_1$ such that $(B_1 \setminus \{q\}) \cup \{q'\} \in \mathcal{B}$.*

Proof. Define the closure operator $\text{cl}(X) = \{q : X\text{-equivalence implies } q\text{-equivalence}\}$. We verify the matroid axioms:

1) **Closure axioms**: cl is extensive, monotone, and idempotent. These follow directly from the definition of logical implication.
2) **Exchange property**: If $q \in \text{cl}(X \cup \{q'\}) \setminus \text{cl}(X)$, then $q' \in \text{cl}(X \cup \{q\})$.

For exchange, take $q \in \text{cl}(X \cup \{q'\}) \setminus \text{cl}(X)$. Since $q \notin \text{cl}(X)$, there exist v, w that are X-equivalent but disagree on q. Because $q \in \text{cl}(X \cup \{q'\})$, any pair that is $(X \cup \{q'\})$-equivalent must agree on q; therefore this witness pair cannot be $(X \cup \{q'\})$-equivalent, so it must disagree on q'. Now fix any pair v', w' that are $(X \cup \{q\})$-equivalent. They are in particular X-equivalent and agree on q. If they disagreed on q', then by the previous implication we could derive disagreement on q, contradiction. Hence v', w' agree on q', proving $q' \in \text{cl}(X \cup \{q\})$.

Minimal distinguishing sets are exactly the bases of the matroid defined by this closure operator. Full machine-checked proof: `proofs/abstract_class_system.lean`, namespace `AxisClosure`. ■

Theorem IV.8 (Matroid bases)**.** *$\mathcal{B}$ is the set of bases of a matroid on ground set E.*

Proof. By the basis-exchange lemma and the standard characterization of matroid bases [12]. ■

Definition IV.9 (Distinguishing dimension)**.** The *distinguishing dimension* of a classification system is the common cardinality of all minimal distinguishing sets.

Remark IV.10 (Ambient attribute count vs. distinguishing dimension). Let $n := |\mathcal{I}|$ be the ambient number of available attributes. Clearly $d \leq n$, and there exist worst-case families with $d = n$.

Corollary IV.11 (Well-defined distinguishing dimension)**.** *All minimal distinguishing sets have equal cardinality. Thus the distinguishing dimension (Definition IV.9) is well-defined.*

D. Implications for Witness Cost

Corollary IV.12 (Lower bound on attribute-only witness cost)**.** *For any attribute-only observer, $W(\textit{class-identity}) \geq d$ where d is the distinguishing dimension.*

Proof. If a procedure queried fewer than d attributes on every execution path, each such queried set would be non-distinguishing by definition of d. For that path, there would exist two different classes with identical answers on all queried attributes, yielding identical transcripts and forcing the same output on both values. This contradicts zero-error class identification. Hence some path requires at least d queries. ■

The key insight: the distinguishing dimension is invariant across all minimal query strategies. The difference between nominal-tag and attribute-only observers lies in *witness cost*: a nominal tag achieves $W = O(1)$ by storing the identity directly, bypassing query enumeration.

V. Witness Cost Analysis

A. Witness Cost for Class Identity

Recall from Section 2 that the witness cost $W(P)$ is the minimum number of primitive queries required to compute property P. For class identity, we ask: what is the minimum number of queries to determine if two values have the same class?

Theorem V.1 (Nominal-Tag Observers Achieve Minimum Witness Cost)**.** *Nominal-tag observers achieve the minimum witness cost for class identity:*

$$W_{eq} = O(1)$$

Specifically, the witness is a single tag read: compare $tag(v_1) = tag(v_2)$.

Attribute-only observers require $W_{eq} = \Omega(d)$ where d is the distinguishing dimension (and $d \leq n$, with worst-case $d = n$).

Proof. See Lean formalization: `proofs/nominal_resolution.lean`. The proof shows:

1) Nominal-tag access is a single primitive query
2) Attribute-only observers must query at least d attributes in the worst case (a generic strategy queries all n)
3) No shorter witness exists for attribute-only observers (by the information barrier)

■

B. Witness Cost Comparison

Observer Class	Witness Procedure	Witness Cost W
Nominal-tag	Single tag read	$O(1)$
Attribute-only	Query a distinguishing set	$\Omega(d)$

TABLE II
WITNESS COST FOR CLASS IDENTITY BY OBSERVER CLASS.

The Lean 4 formalization (Appendix A) provides a machine-checked proof that nominal-tag access minimizes witness cost for class identity.

VI. (L, W, D) Optimality

A. Three-Dimensional Tradeoff: Tag Length, Witness Cost, Distortion

Recall from Section 2 that observer strategies are characterized by three dimensions:

- **Tag length** L: bits required to encode a class identifier ($L \geq \log_2 k$ for k classes under full class tagging)
- **Witness cost** W: minimum number of primitive queries for class identification
- **Distortion** D: probability of misclassification, $D = \Pr[\hat{C} \neq C]$.

We compare two observer classes:

Definition VI.1 (Attribute-only observer)**.** An observer that queries only attribute membership ($q_I \in \Phi_{\mathcal{I}}$), with no access to explicit class tags.

Definition VI.2 (Nominal-tag observer)**.** An observer that may read a single class identifier (nominal tag) per value, in addition to attribute queries.

Theorem VI.3 (Pareto Optimality of Nominal-Tag Observers)**.** *Let A_π be the collision multiplicity (Definition II.28). Then:*

1) *Any $D = 0$ scheme must satisfy $L \geq \log_2 A_\pi$ (Theorem II.30).*
2) *In maximal-barrier domains ($A_\pi = k$), nominal-tag observers achieve the unique Pareto-optimal $D = 0$ point:*
   - ***Tag length**: $L = \lceil \log_2 k \rceil$ bits for k classes*
   - ***Witness cost**: $W = O(1)$ queries (one tag read)*
   - ***Distortion**: $D = 0$ (zero misclassification probability)*
3) *In general (non-maximal) domains, nominal tagging remains Pareto-optimal at $D = 0$ but need not be unique: partial tags can coexist on the frontier.*

In information-barrier domains, attribute-only observers (the $L = 0$ face) satisfy:

- ***Tag length**: $L = 0$ bits (no explicit tag)*
- ***Witness cost**: $W = \Omega(d)$ queries (must query at least one minimal distinguishing set of size d, see Definition IV.9)*
- ***Distortion**: $D > 0$ (probability of misclassification is strictly positive due to collisions)*

Proof. Converse item (1) is Theorem II.30. For item (2), maximal barrier means all classes are observationally colliding, so any $D = 0$ scheme must carry full class identity in tag bits (Corollary II.31), while nominal tags realize this lower bound with one tag read. Pareto uniqueness follows because any competing $D = 0$ point cannot reduce L below $\log_2 k$ nor reduce W below constant-time tag access under the admissibility rules of Section II.

The counting converse and maximal-barrier corollary are machine-checked in Lean: `proofs/lwd_converse.lean`. Runtime cost instantiations (e.g., unbounded gap examples) remain in `proofs/python_instantiation.lean`. ■

Remark VI.4 (General $D = 0$ Frontier). When $1 < A_\pi < k$, the $D = 0$ frontier can include mixed designs: a partial tag identifies collision blocks and queries resolve within blocks. This does not contradict nominal optimality; it only removes global uniqueness outside maximal-barrier domains.

1) Maximal barrier ($A_\pi = k$): unique $D = 0$ nominal point.
2) Intermediate barrier ($1 < A_\pi < k$): multiple $D = 0$ Pareto points may exist.
3) No barrier ($A_\pi = 1$): $L = 0$ zero-error identification is feasible.

B. Pareto Frontier

The three-dimensional frontier shows:

- In maximal-barrier domains, the unique $D = 0$ Pareto point is nominal tagging at $L = \lceil \log_2 k \rceil$.
- In general domains, attribute-only observers trade tag length for distortion on the $L = 0$ face when collisions are present.

Figure 1 visualizes the (L, W, D) tradeoff space. The key observation is the ambiguity converse: the minimum zero-error tag rate is $\log_2 A_\pi$, with the maximal-barrier special case $\log_2 k$.

The Lean 4 formalization (Appendix A) machine-checks the ambiguity-based converse and maximal-barrier lower bound that anchor this tradeoff analysis.

Remark VI.5 (Programming language instantiations). In programming language terms: *nominal typing* corresponds to nominal-tag observers (e.g., CPython's `isinstance`, Java's `.getClass()`). *Duck typing* corresponds to attribute-only observers (e.g., Python's `hasattr`). *Structural typing* is an intermediate case with $D = 0$ but $W = O(n)$.

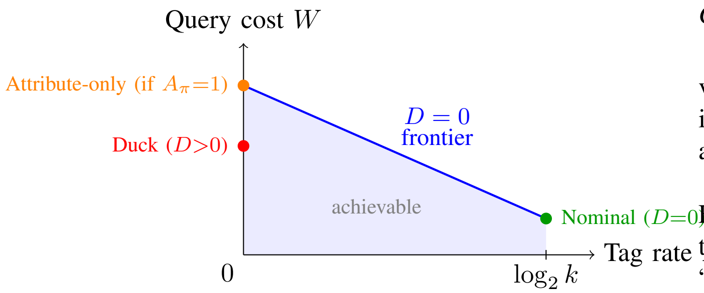

Fig. 1. Schematic illustration of the (L, W, D) tradeoff. For a concrete example with $k = 1000$ classes, distinguishing dimension $d = 10$, and maximal barrier ($A_\pi = k$), the nominal-tag strategy achieves $L = 10$ bits, $W = O(1)$, $D = 0$, while the attribute-only strategy requires $W = 10$ queries and incurs $D > 0$ due to collisions.

Remark VI.6 (Structural-check cost parameter). When structural typing checks traverse s members/fields (rather than ranging over the full attribute universe), the natural bound is $W = O(s)$ with $s \leq n$.

VII. Cross-Domain Instantiations

The preceding sections established abstract information-theoretic results (Sections II–VI). This section provides secondary cross-domain illustrations. The mathematics is unchanged by domain; these examples only instantiate the same observer-model primitives.

A. Biological Taxonomy: Phenotype vs Genotype

Linnean taxonomy classifies organisms by observable phenotypic characters: morphology, behavior, habitat. This is attribute-only observation. The information barrier applies: phenotypically identical organisms from distinct species are indistinguishable.

The cryptic species problem: Cryptic species share identical phenotypic profiles but are reproductively isolated and genetically distinct. Attribute-only observation (morphology) cannot distinguish them: $\pi(A) = \pi(B)$ but $\text{species}(A) \neq \text{species}(B)$.

The nominal tag: DNA barcoding provides the resolution [13]. A short genetic sequence (e.g., mitochondrial COI) acts as the nominal tag: $O(1)$ identity verification via sequence comparison. This reduced cryptic species identification from $\Omega(s)$ phenotypic examination (checking s characters) to constant-time molecular lookup.

B. Library Classification: Subject vs ISBN

Library classification systems like Dewey Decimal observe subject matter, a form of attribute-only classification. Two books on the same subject are indistinguishable by subject code alone.

The nominal tag: The ISBN (International Standard Book Number) is the nominal tag [14]. Given two physical books, identity verification is $O(1)$: compare ISBNs. Without ISBNs, distinguishing two copies of different editions on the same subject requires $O(s)$ attribute inspection (publication date, page count, publisher, etc.).

C. Database Systems: Columns vs Primary Keys

In big-data systems, relational databases observe entities via column values. The information barrier applies: rows with identical column values, excluding the key, are indistinguishable.

The nominal tag: The primary key is the nominal tag [15]. Entity identity is $O(1)$: compare keys. This is why database theory requires keys—without them, the system cannot answer "is this the same entity?"

Natural vs surrogate keys: Natural keys (composed of attributes) are attribute-only observation and inherit its limitations. Surrogate keys (auto-increment IDs, UUIDs) are pure nominal tags: no semantic content, pure identity.

D. Programming-Language Snapshot (Secondary Illustration)

Programming-language runtimes are one instantiation of the same abstraction, not the source of the theory. Table III summarizes the mapping from runtime mechanisms to (L, W, D) model primitives.

Runtime	Nominal mechanism	Identity cost
CPython	`ob_type` / `type(a) is type(b)` [16]	$O(1)$
Java	class tag via `.getClass()` / `instanceof` [17], [18]	$O(1)$ to $O(d)$
TypeScript	structural compatibility only [19]	$O(s)$
Rust	`TypeId` for nominal identity [20]	$O(1)$

TABLE III
PROGRAMMING-LANGUAGE SNAPSHOT AS A SECONDARY ILLUSTRATION OF THE ABSTRACT OBSERVER MODEL.

Without a class tag, identity checks are structural and scale with inspected structure size ($O(s)$). With a class tag, identity is constant-time (or near-constant with bounded hierarchy traversal). This is exactly the generic witness-cost separation from Sections V and VI.

E. Cross-Domain Summary

Domain	Attribute-Only	Nominal Tag	W
Biology	Phenotype (morphology)	DNA barcode (COI)	$O(1)$
Libraries	Subject (Dewey)	ISBN	$O(1)$
Databases	Column values	Primary key	$O(1)$
CPython	`hasattr` probing	`ob_type` pointer	$O(1)$
Java	Attribute/interface check	`.getClass()`	$O(1)$
TypeScript	Structural check	(none at runtime)	$O(s)$
Rust (static)	Trait bounds	`TypeId`	$O(1)$

TABLE IV
WITNESS COST FOR IDENTITY ACROSS CLASSIFICATION SYSTEMS. NOMINAL TAGS ACHIEVE $O(1)$; ATTRIBUTE-ONLY PAYS $O(s)$ PER STRUCTURAL CHECK (OR $O(k)$ WHEN ENUMERATING CLASSES UNDER DECLARED ATTRIBUTE CATALOGS, E.G., INTERFACES IN PL RUNTIMES).

The pattern is universal: systems with nominal tags achieve $O(1)$ witness cost; systems without them pay $O(s)$ or $O(k)$. This is not domain-specific; it is the information barrier theorem instantiated across classification systems.

F. Machine Learning: Model Identification and Versioning

Neural network models in production systems face the identification problem: given two model instances, determine if they represent the same architecture. Model registries must compress model metadata while enabling efficient identification.

Attribute-only approach: Compare architecture fingerprints (layer counts, activation functions, parameter counts, connectivity patterns). Cost: $O(s)$ where s is the number of architectural features.

Nominal tag: Model hash (e.g., SHA-256 of architecture definition) or registry ID. Cost: $O(1)$.

The (L, W, D) tradeoff applies directly: storing $\lceil \log_2 k \rceil$ bits per model (where k is the number of distinct architectures in the registry) enables $O(1)$ identification with $D = 0$. Attribute-based versioning requires $\Omega(d)$ feature comparisons and risks false positives ($D > 0$) when architectures share identical fingerprints but differ in subtle structural details.

Example: A model registry with $k = 10^6$ architectures requires only 20 bits per model for perfect identification via nominal tags, versus $O(d)$ queries over potentially hundreds of architectural features for attribute-based approaches.

VIII. Extensions

A. Noisy Query Model

Throughout this paper, queries are deterministic: $q_I(v) \in \{0, 1\}$ is a fixed function of v. In practice, observations may be corrupted. We sketch an extension to noisy queries and state the resulting open problems.

Definition VIII.1 (Noisy observation channel)**.** A *noisy observation channel* with crossover probability $\epsilon \in [0, 1/2)$ returns:

$$\tilde{q}_I(v) = \begin{cases} q_I(v) & \text{with probability } 1 - \epsilon \\ 1 - q_I(v) & \text{with probability } \epsilon \end{cases}$$

Each query response is an independent BSC(ϵ) corruption of the true value.

Definition VIII.2 (Noisy identification capacity)**.** The *ϵ-noisy identification capacity* is the supremum rate (in bits per entity) at which zero-error identification is achievable when all attribute queries pass through a BSC(ϵ).

In the noiseless case ($\epsilon = 0$), Theorem II.11 shows the capacity is binary: $\log_2 k$ if π is class-injective, 0 otherwise. For $\epsilon > 0$, several questions arise.

Open problem (noisy identification cost). For $\epsilon > 0$ and class-injective π, zero-error identification is impossible with finite queries (since BSC has nonzero error probability). With bounded error $\delta > 0$, we expect the identification cost to scale as $W = \Theta\left(\frac{\log(1/\delta)}{(1-2\epsilon)^2}\right)$ queries per entity. A key observation is that a nominal tag of $L \geq \lceil \log_2 k \rceil$ bits (transmitted noiselessly) should restore $O(1)$ identification regardless of query noise.

The third point is the key insight: *nominal tags provide a noise-free side channel*. Even when attribute observations are corrupted, a clean tag enables $O(1)$ identification. This strengthens the case for nominal tagging in noisy environments, precisely the regime where "duck typing" would require many repeated queries to achieve confidence.

Connection to identification via channels. The noisy model connects more directly to Ahlswede-Dueck identification [1]. In their framework, identification capacity over a noisy channel can exceed Shannon capacity (double-exponential codebook sizes). Our setting differs: we have *adaptive queries* rather than block codes, and the decoder must identify a *class* rather than test a hypothesis. Characterizing the interplay between adaptive query strategies and channel noise is an open problem.

B. Rate-Distortion-Query Tradeoff Surface

The (L, W, D) tradeoff admits a natural geometric interpretation. In the maximal-barrier regime we identify a unique Pareto-optimal point at $D = 0$ (Theorem VI.3); outside that regime, the full tradeoff surface can contain multiple $D = 0$ frontier points.

Fixed-W slices. For fixed query budget W, what is the minimum tag rate L to achieve distortion D? When $W \geq d$ (the distinguishing dimension), zero distortion is achievable with $L = 0$ via exhaustive querying. When $W < d$, the observer cannot distinguish all classes, and either:

- Accept $D > 0$ (misidentification), or
- Add tags ($L > 0$) to compensate for insufficient queries.

Fixed-L slices. For fixed tag rate $L < \log_2 k$, the tag partitions the k classes into 2^L groups. Within each group, the observer must use queries to distinguish. The query cost is determined by the distinguishing dimension *within each group*, which is potentially much smaller than the global dimension.

Open problem (subadditivity of query cost). For a tag of rate L partitioning classes into groups $G_1, \ldots, G_{2^L}$, we expect $W(L) \leq \max_i d(G_i)$, where $d(G_i)$ is the distinguishing dimension within group G_i. Optimal tag design should minimize this maximum. Characterizing the optimal partition remains open.

C. Semantic Distortion Measures

We have treated distortion D as binary (correct identification or not). Richer distortion measures are possible:

- **Hierarchical distortion**: Misidentifying a class within the same genus (biological) or module (type system) is less severe than cross-genus errors.
- **Weighted distortion**: Some misidentifications have higher cost than others (e.g., type errors causing security vulnerabilities vs. benign type confusion).

D. Privacy and Security

Privacy-preserving identification. Nominal tags enable zero-knowledge proofs of class membership without revealing attribute profiles. An entity can prove "I belong to class C" by revealing $\tau(v) = C$ without exposing $\pi(v)$, preserving attribute privacy. Attribute-only schemes must reveal the complete profile $\pi(v)$ to prove membership, leaking structural information.

Secure model verification. In machine learning deployment, compressed model identifiers prevent model substitution attacks. Verifying model identity via nominal tags ($O(1)$ hash comparison) is more efficient and secure than attribute-based verification ($O(s)$ architecture inspection), which is vulnerable to adversarial perturbations that preserve structural fingerprints while altering behavior.

E. Connection to Rate-Distortion-Perception Theory

Blau and Michaeli [5] extended classical rate-distortion theory by adding a *perception* constraint: the reconstructed distribution must match a target distribution under some divergence measure. This creates a three-way tradeoff between rate, distortion, and perceptual quality.

Our (L, W, D) framework admits a parallel interpretation. The query cost W plays a role analogous to the perception constraint: it measures the *interactive cost* of achieving low distortion, rather than a distributional constraint. Just as rate-distortion-perception theory asks "what is the minimum rate to achieve distortion D while satisfying perception constraint P?", we ask "what is the minimum tag rate L to achieve distortion D with query budget W?"

The analogy suggests several directions:

- **Perception as identification fidelity**: In classification systems that must preserve statistical properties (e.g., sampling from a type distribution), a perception constraint would require the observer's class estimates to have the correct marginal distribution, not just low expected error.
- **Three-resource tradeoffs**: The (L, W, D) Pareto frontier (Theorem VI.3) is a discrete analogue of the rate-distortion-perception tradeoff surface. Characterizing this surface for specific classification problems would extend the geometric rate-distortion program to identification settings.

Formalizing these connections would unify identification capacity with the broader rate-distortion-perception literature.

IX. Conclusion

This paper presents an information-theoretic analysis of classification under observational constraints. We prove three main results:

1) **Information Barrier**: Observers limited to attribute-membership queries cannot compute properties that vary within indistinguishability classes. This is universal: it applies to biological taxonomy, database systems, library classification, and programming language runtimes alike.
2) **Witness Optimality**: Nominal-tag observers achieve $W(\text{identity}) = O(1)$, the minimum witness cost. The gap from attribute-only observation ($\Omega(d)$, with a worst-case family where $d = n$) is unbounded.
3) **Matroid Structure**: Minimal distinguishing query sets form the bases of a matroid. The distinguishing dimension of a classification problem is well-defined and computable.

A. The Universal Pattern

Across domains, the same structure recurs:

- **Biology**: Phenotypic observation cannot distinguish cryptic species. DNA barcoding (nominal tag) resolves them in $O(1)$.
- **Databases**: Column-value queries cannot distinguish rows with identical attributes. Primary keys (nominal tag) provide $O(1)$ identity.
- **Type systems**: Attribute observation (interfaces/method signatures in this instantiation) cannot distinguish structurally identical types. Type tags provide $O(1)$ identity.

The information barrier is not a quirk of any particular domain; it is a mathematical necessity arising from the quotient structure induced by limited observations.

B. Implications

- **The necessity of nominal information is a theorem, not a preference.** Any zero-error scheme must satisfy the ambiguity converse $L \geq \log_2 A_\pi$ (Theorem II.30), where A_π is the largest collision block induced by observable profiles. In maximal-barrier domains ($A_\pi = k$), this becomes $L \geq \log_2 k$ and nominal tagging gives the unique $D = 0$ Pareto point with $W = O(1)$ (Theorem VI.3).
- **The barrier is informational, not computational**: even with unbounded resources, attribute-only observers cannot overcome it.
- **Fixed-axis systems are necessarily incomplete outside their axis**: by Corollary II.6, any fixed-axis classifier is complete only for axis-measurable properties and cannot represent properties that vary within an axis fiber unless a new axis/tag is introduced.
- **Classification system design is constrained**: the choice of observation family determines which properties are computable.

C. Future Work

1) **Other classification domains**: What is the matroid structure of observation spaces in chemistry (molecular fingerprints), linguistics (phonetic features), or machine learning (feature embeddings)?
2) **Witness complexity of other properties**: Beyond identity, what are the witness costs for provenance, equivalence, or subsumption?
3) **Hybrid observers**: Can observer strategies that combine tags and attributes achieve better (L, W, D) tradeoffs for specific query distributions?

D. Conclusion

Classification under observational constraints admits a clean information-theoretic analysis. The zero-error converse is governed by collision multiplicity: any $D = 0$ scheme necessarily has $L \geq \log_2 A_\pi$ (Theorem II.30). In maximal-barrier domains ($A_\pi = k$), nominal-tag observation achieves the unique Pareto-optimal $D = 0$ point in the (L, W, D) tradeoff (Theorem VI.3). The results are universal within the stated observation model, and all proofs are machine-verified in Lean 4.

AI Disclosure

This work was developed with AI assistance (Claude, Anthropic). The AI contributed to exposition, code generation, and proof exploration. All mathematical claims were verified by the authors and machine-checked in Lean 4. The Lean proofs are the authoritative source; no theorem depends solely on AI-generated reasoning.

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Appendix

A. Formalization and Verification

The core claims in this paper are machine-checked in Lean 4. We keep the appendix concise for JSAIT and move full operational listings and implementation-level proof scripts to the supplementary artifact.

a) What is in scope in the mechanization.: The formalization covers the abstract observer model, the information barrier, constant-witness vs. query lower-bound separation, matroid structure of minimal distinguishing query sets, and the (L, W, D) zero-error frontier claims stated in the main text.

b) What is moved to supplementary artifact.: Implementation-specific operational details and extended code listings are included in supplementary material and are not required to follow the IT contribution in the main paper.

c) Artifact totals.: The complete artifact contains 14 Lean files totaling 6589 lines and 296 theorem/lemma statements; the table above highlights the core modules directly used by the main-text derivations.

B. Attribute-Only Formalization

Attribute-only observation is formalized by an equivalence relation on values induced by observable query responses.

```
structure InterfaceValue where
  fields : List (String * Nat)
deriving DecidableEq

def getField (obj : InterfaceValue) (name :
    String) : Option Nat :=
  match obj.fields.find? (fun p => p.1 == name)
    with
  | some p => some p.2 | none => none

def interfaceEquivalent (a b : InterfaceValue) :
    Prop :=
  forall name, getField a name = getField b name

def InterfaceRespecting (f : InterfaceValue -> a)
    : Prop :=
  forall a b, interfaceEquivalent a b -> f a = f b
```

C. Corollary 6.3: Provenance Impossibility

Under attribute-only observation, provenance is constant on attribute-equivalence classes; therefore provenance cannot be recovered when distinct classes collide under the observable profile.

```
theorem interface_provenance_indistinguishable
    (getProvenance : InterfaceValue -> Option
    DuckProvenance)
    (h_interface : InterfaceRespecting
    getProvenance)
    (obj1 obj2 : InterfaceValue)
    (h_equiv : interfaceEquivalent obj1 obj2) :
    getProvenance obj1 = getProvenance obj2 :=
  h_interface obj1 obj2 h_equiv
```

This is the mechanized form of the main-text impossibility statement: if an observer factors through attribute profile alone, it cannot separate equal-profile values by source/provenance.

D. Abstract Model Lean Formalization

The abstract model is formalized directly at the axis level and then connected to concrete instantiations.

```
-- Axis-indexed representation
abbrev Typ (A : Finset Axis) := (a : Axis) -> a
    \in A -> axisType a

-- Two-axis setting used in the paper
abbrev Typ2 := Typ ({Axis.Bases, Axis.Shape} :
    Finset Axis)

-- Projectors
abbrev projBases (t : Typ2) := t Axis.Bases (by
    simp)
abbrev projShape (t : Typ2) := t Axis.Shape (by
    simp)
```

The corresponding isomorphism theorem establishes that the two-axis representation is complete for in-scope observables in the formal model.

TABLE V
LEAN 4 FORMALIZATION MODULES

Module	Lines	Theorems	Purpose
abstract_class_system.lean	3278	155	Two-axis instantiation, barrier, dominance
axis_framework.lean	1721	63	Query families, closure, matroid structure
nominal_resolution.lean	609	27	Nominal identification and witness procedures
discipline_migration.lean	142	11	Discipline vs. migration consequences
context_formalization.lean	215	7	Greenfield/retrofit context model
python_instantiation.lean	249	17	Python instantiation
typescript_instantiation.lean	65	4	TypeScript instantiation
java_instantiation.lean	63	4	Java instantiation
rust_instantiation.lean	64	4	Rust instantiation
lwd_converse.lean	41	4	Ambiguity converse counting lemmas
Core modules subtotal	**6447**	**296**	**10 representative modules shown**

E. Reproducibility

The full Lean development is provided in supplementary material. To verify locally:

1) Install Lean 4 and Lake (https://leanprover.github.io/).
2) From the release package root, run:

```
cd proofs
lake build
```

3) Confirm successful build with no `sorry` placeholders.