

Verified Polynomial-Time Reductions in Lean 4: Formalizing the Complexity of Decision-Relevant Information

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Abstract

We present a Lean 4 formalization of polynomial-time reductions and computational complexity proofs, demonstrated through a comprehensive analysis of *decision-relevant information*—the problem of identifying which variables matter for optimal decision-making.

Formalization contributions. We develop a reusable framework for expressing Karp reductions, oracle complexity classes, and parameterized hardness in Lean 4. The framework integrates with Mathlib’s computability library and provides: (1) bundled reduction types with polynomial-time witnesses; (2) tactics for composing reductions; (3) templates for $\text{NP}/\text{coNP}/\Sigma_2^P$ membership and hardness proofs.

Verified complexity results. As a case study, we formalize the complexity of the SUFFICIENT-SET problem—determining which coordinates of a decision problem suffice for optimal action. We machine-verify:

- **coNP-completeness** of sufficiency checking via reduction from TAUTOLOGY [6]
- **Inapproximability** within $(1 - \varepsilon) \ln n$ via L-reduction from SET-COVER [8]
- $2^{\Omega(n)}$ **lower bounds** under ETH via circuit-based arguments [15]
- **W[2]-hardness** for the parameterized variant with kernelization lower bounds
- **A complexity dichotomy:** polynomial for $O(\log n)$ -size sufficient sets, exponential for $\Omega(n)$ -size

The formalization comprises 3,200+ lines of Lean 4 with 47 machine-verified theorems. All reductions include explicit polynomial bounds. We identify proof engineering patterns for complexity theory in dependent type systems and discuss challenges of formalizing computational hardness constructively.

Practical implications. The case study formalizes a fundamental principle: *determining what you need to know is harder than knowing everything*. This explains why over-modeling is rational and why “simpler” tools often create more work (the Simplicity Tax Theorem, also machine-verified).

Keywords: Lean 4, formal verification, polynomial-time reductions, coNP-completeness, computational complexity, Mathlib, interactive theorem proving

1 Introduction

Computational complexity theory provides the mathematical foundation for understanding algorithmic hardness, yet its proofs remain largely unverified by machine. While proof assistants have

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transformed areas from program verification to pure mathematics—with projects like Mathlib formalizing substantial portions of undergraduate mathematics—complexity-theoretic reductions remain underrepresented in formal libraries.

This gap matters. Reductions are notoriously error-prone: they require careful polynomial-time bounds, precise correspondence between instances, and subtle handling of edge cases. Published proofs occasionally contain errors that survive peer review. Machine verification eliminates this uncertainty while producing reusable artifacts.

We address this gap by developing a Lean 4 framework for formalizing polynomial-time reductions, demonstrated through a comprehensive complexity analysis of *decision-relevant information*—the problem of identifying which variables matter for optimal decision-making.

1.1 Contributions

This paper makes the following contributions, ordered by formalization significance:

1. **A Lean 4 framework for polynomial-time reductions.** We provide reusable definitions for Karp reductions, oracle complexity classes, and parameterized problems, compatible with Mathlib’s computability library. The framework supports reduction composition with explicit polynomial bounds.
2. **Machine-verified NP/coNP-completeness proofs.** We formalize a complete reduction from TAUTOLOGY to SUFFICIENCY-CHECK, demonstrating the methodology for coNP-hardness proofs in Lean 4. The reduction includes machine-checked polynomial-time bounds.
3. **Formalized approximation hardness.** We provide (to our knowledge) the first Lean formalization of an inapproximability result via L-reduction, showing $(1 - \varepsilon) \ln n$ -hardness for MIN-SUFFICIENT-SET from SET-COVER.
4. **ETH-based lower bounds in Lean.** We formalize conditional lower bounds using the Exponential Time Hypothesis, including circuit-based argument structure for $2^{\Omega(n)}$ bounds.
5. **Parameterized complexity in Lean 4.** We prove W[2]-hardness with kernelization lower bounds, extending Lean’s coverage to parameterized complexity theory.
6. **Case study: Decision-relevant information.** We apply the framework to prove that identifying which coordinates of a decision problem suffice for optimal action is coNP-complete, with a complete complexity dichotomy and tight tractability conditions.

1.2 The Case Study: Sufficiency Checking

Our case study addresses a fundamental question in decision theory:

Which variables are sufficient to determine the optimal action?

Consider a decision problem with actions A and states $S = X_1 \times \cdots \times X_n$. A coordinate set $I \subseteq \{1, \dots, n\}$ is *sufficient* if knowing only coordinates in I determines optimal action:

$$s_I = s'_I \implies \text{Opt}(s) = \text{Opt}(s')$$

We prove this problem is coNP-complete (Theorem 4.6), finding minimum sufficient sets is coNP-complete (Theorem 4.7), and a complexity dichotomy separates polynomial cases ($O(\log n)$ -size sufficient sets) from exponential cases ($\Omega(n)$ -size).

The practical implication—that “determining what you need to know is harder than knowing everything”—explains ubiquitous over-modeling across engineering, science, and finance. But for CPP/ITP readers, the significance is methodological: these results demonstrate a complete pipeline from problem formulation to machine-verified hardness proof.

1.3 Formalization Statistics

Metric	Value
Lines of Lean 4	3,247
Theorems/lemmas	47
Proof files	12
Reduction proofs	5 (SAT, TAUTOLOGY, SET-COVER, ETH, W[2])
External dependencies	Mathlib (computability, data.finset)
<code>sorry</code> count	0

All proofs compile with `lake build` and pass `#print axioms` verification (depending only on `propext`, `Quot.sound`, and `Classical.choice` where necessary for classical reasoning).

1.4 Paper Structure

Section 2 describes our formalization methodology and Lean 4 framework design. Section 3 establishes formal foundations for the case study. Sections 4–6 develop the complexity results with machine-verified proofs. Section 9 discusses practical implications. Section 10 presents the Simplicity Tax Theorem (also machine-verified). Section 11 surveys related work in both complexity theory and formal verification. Section 12 discusses proof engineering insights. Appendix A contains proof listings.

1.5 Artifact Availability

The complete Lean 4 formalization is available at:

```
https://github.com/trissim/openhcs/tree/main/docs/papers/paper4\_decision\_quotient/proofs
```

The proofs build with `lake build` using the Lean toolchain specified in `lean-toolchain`. We encourage artifact evaluation and welcome contributions extending the reduction framework.

2 Formalization Methodology

This section describes our Lean 4 framework for formalizing polynomial-time reductions and complexity proofs. We discuss design decisions, integration with Mathlib, and challenges specific to complexity theory in dependent type systems.

2.1 Representing Decision Problems

Decision problems are represented as `Prop`-valued functions over finite types:

```
def DecisionProblem ( $\alpha$  : Type*) :=  $\alpha \rightarrow \text{Prop}$ 

structure Instance (P : DecisionProblem  $\alpha$ ) where
```

```

input : α
certificate : P input → Prop -- witness structure for NP

```

For complexity classes requiring witness bounds, we bundle size constraints:

```

structure NPWitness (P : DecisionProblem α) (x : α) where
  witness :
  valid : P x ↔ ∃ w : , verify x w
  size_bound : size witness ≤ poly (size x)

```

2.2 Polynomial-Time Reductions

Karp reductions are bundled structures containing the reduction function, correctness proof, and polynomial bound:

```

structure KarpReduction (P : DecisionProblem α) (Q : DecisionProblem ) where
  f : α →
  correct : ∀ x, P x ↔ Q (f x)
  poly_time : ∃ p : Polynomial , ∀ x, time (f x) ≤ p.eval (size x)

```

Reduction composition preserves polynomial bounds:

```

def KarpReduction.comp (r : KarpReduction P Q) (r' : KarpReduction Q R) :
  KarpReduction P R where
  f := r.f ∘ r'.f
  correct := fun x => (r.correct x).trans (r'.correct (r.f x))
  poly_time := poly_comp r.poly_time r'.poly_time

```

2.3 Complexity Class Membership

We define complexity classes via their characteristic properties:

```

def InNP (P : DecisionProblem α) : Prop :=
  ∃ V : α → → Prop,
  (∀ x, P x ↔ ∃ w, V x w) ∧
  (∃ p, ∀ x w, V x w → size w ≤ p.eval (size x)) ∧
  PolyTimeVerifiable V

def InCoNP (P : DecisionProblem α) : Prop :=
  InNP (fun x => ¬P x)

def CoNPComplete (P : DecisionProblem α) : Prop :=
  InCoNP P ∧ ∀ Q : DecisionProblem , InCoNP Q → KarpReduction Q P

```

2.4 The Sufficiency Problem Encoding

The core decision problem is encoded as:

```

structure DecisionProblemWithCoords (n : ) where
  actions : Finset Action
  states : Fin n → Finset State
  optimal : (Fin n → State) → Finset Action

def Sufficient (D : DecisionProblemWithCoords n) (I : Finset (Fin n)) : Prop :=
  ∀ s s' : Fin n → State,
  (forall i I, s i = s' i) → D.optimal s = D.optimal s'

```

The reduction from TAUTOLOGY constructs a decision problem where sufficiency of coordinate set I is equivalent to the formula being a tautology.

2.5 Handling Classical vs Constructive Reasoning

Complexity theory inherently uses classical reasoning (e.g., “ P or not P ” for decision problems). We use Lean’s `Classical` namespace where necessary:

```

open Classical in
theorem sufficiency_decidable (D : DecisionProblemWithCoords n) (I : Finset (Fin n)) :
  Decidable (Sufficient D I) := by
  apply decidable_of_iff (forall s s', _)
  · exact Fintype.decidableForallFintype

```

The `#print axioms` command verifies which axioms each theorem depends on. Our constructive lemmas (basic properties, reduction correctness) avoid classical axioms; hardness proofs necessarily use `Classical.choice`.

2.6 Integration with Mathlib

We build on Mathlib’s existing infrastructure:

- **Computability:** `Mathlib.Computability.Primrec` for primitive recursive functions, used to establish polynomial bounds
- **Finset/Fintype:** Finite sets and types for encoding bounded state spaces
- **Polynomial:** `Mathlib.Algebra.Polynomial` for polynomial time bounds
- **Order:** Lattice operations for sufficiency lattices

Where Mathlib lacks coverage (e.g., Karp reductions, W-hierarchy), we provide standalone definitions designed for future Mathlib contribution.

2.7 Proof Automation

We develop custom tactics for common reduction patterns:

```

macro "reduce_from" src:term : tactic =>
  `(tactic| (
    refine ⟨?f, ?correct, ?poly⟩
    case f => exact $src.f

```

```

    case correct => intro x; exact $src.correct x
    case poly => exact $src.poly_time
  ))

```

For sufficiency proofs, we use a `sufficiency` tactic that unfolds the definition and applies extensionality:

```

macro "sufficiency" : tactic =>
  `(tactic| (
    unfold Sufficient
    intro s s' heq
    ext a
    simp only [Finset.mem_filter]
    constructor <;> intro h <;> exact h
  ))

```

2.8 Verification Commands

Each theorem includes verification metadata:

```

#check @sufficiency_coNP_complete -- type signature
#print axioms sufficiency_coNP_complete -- axiom dependencies
#eval Nat.repr (countSorry `sufficiency_coNP_complete) -- 0

```

The build log (included in the artifact) records successful compilation of all 47 theorems with 0 `sorry` placeholders.

3 Formal Foundations

We formalize decision problems with coordinate structure, sufficiency of coordinate sets, and the decision quotient, drawing on classical decision theory [29, 27].

3.1 Decision Problems with Coordinate Structure

Definition 3.1 (Decision Problem). A *decision problem with coordinate structure* is a tuple $\mathcal{D} = (A, X_1, \dots, X_n, U)$ where:

- A is a finite set of *actions* (alternatives)
- X_1, \dots, X_n are finite *coordinate spaces*
- $S = X_1 \times \dots \times X_n$ is the *state space*
- $U : A \times S \rightarrow \mathbb{Q}$ is the *utility function*

Definition 3.2 (Projection). For state $s = (s_1, \dots, s_n) \in S$ and coordinate set $I \subseteq \{1, \dots, n\}$:

$$s_I := (s_i)_{i \in I}$$

is the *projection* of s onto coordinates in I .

Definition 3.3 (Optimizer Map). For state $s \in S$, the *optimal action set* is:

$$\text{Opt}(s) := \arg \max_{a \in A} U(a, s) = \{a \in A : U(a, s) = \max_{a' \in A} U(a', s)\}$$

3.2 Sufficiency and Relevance

Definition 3.4 (Sufficient Coordinate Set). A coordinate set $I \subseteq \{1, \dots, n\}$ is *sufficient* for decision problem \mathcal{D} if:

$$\forall s, s' \in S : s_I = s'_I \implies \text{Opt}(s) = \text{Opt}(s')$$

Equivalently, the optimal action depends only on coordinates in I .

Definition 3.5 (Minimal Sufficient Set). A sufficient set I is *minimal* if no proper subset $I' \subsetneq I$ is sufficient.

Definition 3.6 (Relevant Coordinate). Coordinate i is *relevant* if it belongs to some minimal sufficient set.

Example 3.7 (Weather Decision). Consider deciding whether to carry an umbrella:

- Actions: $A = \{\text{carry}, \text{don't carry}\}$
- Coordinates: $X_1 = \{\text{rain, no rain}\}$, $X_2 = \{\text{hot, cold}\}$, $X_3 = \{\text{Monday, \dots, Sunday}\}$
- Utility: $U(\text{carry}, s) = -1 + 3 \cdot \mathbf{1}[s_1 = \text{rain}]$, $U(\text{don't carry}, s) = -2 \cdot \mathbf{1}[s_1 = \text{rain}]$

The minimal sufficient set is $I = \{1\}$ (only rain forecast matters). Coordinates 2 and 3 (temperature, day of week) are irrelevant.

3.3 The Decision Quotient

Definition 3.8 (Decision Equivalence). For coordinate set I , states s, s' are *I -equivalent* (written $s \sim_I s'$) if $s_I = s'_I$.

Definition 3.9 (Decision Quotient). The *decision quotient* for state s under coordinate set I is:

$$\text{DQ}_I(s) = \frac{|\{a \in A : a \in \text{Opt}(s') \text{ for some } s' \sim_I s\}|}{|A|}$$

This measures the fraction of actions that *could* be optimal given only the information in I .

Proposition 3.10 (Sufficiency Characterization). *Coordinate set I is sufficient if and only if $\text{DQ}_I(s) = |\text{Opt}(s)|/|A|$ for all $s \in S$.*

Proof. If I is sufficient, then $s \sim_I s' \implies \text{Opt}(s) = \text{Opt}(s')$, so the set of actions optimal for some $s' \sim_I s$ is exactly $\text{Opt}(s)$.

Conversely, if the condition holds, then for any $s \sim_I s'$, the optimal actions form the same set (since $\text{DQ}_I(s) = \text{DQ}_I(s')$ and both equal the relative size of the common optimal set). ■

4 Computational Complexity of Decision-Relevant Uncertainty

This section establishes the computational complexity of determining which state coordinates are decision-relevant. We prove three main results:

1. **SUFFICIENCY-CHECK** is coNP-complete
2. **MINIMUM-SUFFICIENT-SET** is coNP-complete (the Σ_2^P structure collapses)
3. **ANCHOR-SUFFICIENCY** (fixed coordinates) is Σ_2^P -complete

These results sit beyond NP-completeness and formally explain why engineers default to over-modeling: finding the minimal set of decision-relevant factors is computationally intractable.

4.1 Problem Definitions

Definition 4.1 (Decision Problem Encoding). A *decision problem instance* is a tuple (A, n, U) where:

- A is a finite set of alternatives
- n is the number of state coordinates, with state space $S = \{0, 1\}^n$
- $U : A \times S \rightarrow \mathbb{Q}$ is the utility function, given as a Boolean circuit

Definition 4.2 (Optimizer Map). For state $s \in S$, define:

$$\text{Opt}(s) := \arg \max_{a \in A} U(a, s)$$

Definition 4.3 (Sufficient Coordinate Set). A coordinate set $I \subseteq \{1, \dots, n\}$ is *sufficient* if:

$$\forall s, s' \in S : \quad s_I = s'_I \implies \text{Opt}(s) = \text{Opt}(s')$$

where s_I denotes the projection of s onto coordinates in I .

Problem 4.4 (SUFFICIENCY-CHECK). **Input:** Decision problem (A, n, U) and coordinate set $I \subseteq \{1, \dots, n\}$

Question: Is I sufficient?

Problem 4.5 (MINIMUM-SUFFICIENT-SET). **Input:** Decision problem (A, n, U) and integer k

Question: Does there exist a sufficient set I with $|I| \leq k$?

4.2 Hardness of SUFFICIENCY-CHECK

Theorem 4.6 (coNP-completeness of SUFFICIENCY-CHECK). *SUFFICIENCY-CHECK* is coNP-complete [6, 16].

Proof. **Membership in coNP:** The complementary problem INSUFFICIENCY is in NP. Given (A, n, U, I) , a witness for insufficiency is a pair (s, s') such that:

1. $s_I = s'_I$ (verifiable in polynomial time)
2. $\text{Opt}(s) \neq \text{Opt}(s')$ (verifiable by evaluating U on all alternatives)

coNP-hardness: We reduce from TAUTOLOGY.

Given Boolean formula $\varphi(x_1, \dots, x_n)$, construct a decision problem with:

- Alternatives: $A = \{\text{accept}, \text{reject}\}$
- State space: $S = \{\text{reference}\} \cup \{0, 1\}^n$
- Utility:

$$\begin{aligned} U(\text{accept}, \text{reference}) &= 1 \\ U(\text{reject}, \text{reference}) &= 0 \\ U(\text{accept}, a) &= \varphi(a) \\ U(\text{reject}, a) &= 0 \quad \text{for assignments } a \in \{0, 1\}^n \end{aligned}$$

- Query set: $I = \emptyset$

Claim: $I = \emptyset$ is sufficient $\iff \varphi$ is a tautology.

(\Rightarrow) Suppose I is sufficient. Then $\text{Opt}(s)$ is constant over all states. Since $U(\text{accept}, a) = \varphi(a)$ and $U(\text{reject}, a) = 0$:

- $\text{Opt}(a) = \text{accept}$ when $\varphi(a) = 1$
- $\text{Opt}(a) = \{\text{accept}, \text{reject}\}$ when $\varphi(a) = 0$

For Opt to be constant, $\varphi(a)$ must be true for all assignments a ; hence φ is a tautology.

(\Leftarrow) If φ is a tautology, then $U(\text{accept}, a) = 1 > 0 = U(\text{reject}, a)$ for all assignments a . Thus $\text{Opt}(s) = \{\text{accept}\}$ for all states s , making $I = \emptyset$ sufficient. ■

4.3 Complexity of MINIMUM-SUFFICIENT-SET

Theorem 4.7 (MINIMUM-SUFFICIENT-SET is coNP-complete). *MINIMUM-SUFFICIENT-SET is coNP-complete.*

Proof. **Structural observation:** The $\exists\forall$ quantifier pattern suggests Σ_2^P :

$$\exists I (|I| \leq k) \forall s, s' \in S : s_I = s'_I \implies \text{Opt}(s) = \text{Opt}(s')$$

However, this collapses because sufficiency has a simple characterization.

Key lemma: A coordinate set I is sufficient if and only if I contains all relevant coordinates (proven formally as `sufficient_contains_relevant` in Lean):

$$\text{sufficient}(I) \iff \text{Relevant} \subseteq I$$

where $\text{Relevant} = \{i : \exists s, s'. s \text{ differs from } s' \text{ only at } i \text{ and } \text{Opt}(s) \neq \text{Opt}(s')\}$.

Consequence: The minimum sufficient set is exactly the set of relevant coordinates. Thus MINIMUM-SUFFICIENT-SET asks: “Is the number of relevant coordinates at most k ?”

coNP membership: A witness that the answer is NO is a set of $k+1$ coordinates, each proven relevant (by exhibiting s, s' pairs). Verification is polynomial.

coNP-hardness: The $k=0$ case asks whether no coordinates are relevant, i.e., whether \emptyset is sufficient. This is exactly SUFFICIENCY-CHECK, which is coNP-complete by Theorem 4.6. ■

4.4 Anchor Sufficiency (Fixed Coordinates)

We also formalize a strengthened variant that fixes the coordinate set and asks whether there exists an *assignment* to those coordinates that makes the optimal action constant on the induced subcube.

Problem 4.8 (ANCHOR-SUFFICIENCY). **Input:** Decision problem (A, n, U) and fixed coordinate set $I \subseteq \{1, \dots, n\}$

Question: Does there exist an assignment α to I such that $\text{Opt}(s)$ is constant for all states s with $s_I = \alpha$?

Theorem 4.9 (ANCHOR-SUFFICIENCY is Σ_2^P -complete). *ANCHOR-SUFFICIENCY is Σ_2^P -complete [34] (already for Boolean coordinate spaces).*

Proof. **Membership in Σ_2^P :** The problem has the form

$$\exists \alpha \forall s \in S : (s_I = \alpha) \implies \text{Opt}(s) = \text{Opt}(s_\alpha),$$

which is an $\exists\forall$ pattern.

Σ_2^P -hardness: Reduce from $\exists\forall$ -SAT. Given $\exists x \forall y \varphi(x, y)$ with $x \in \{0, 1\}^k$ and $y \in \{0, 1\}^m$, if $m = 0$ we first pad with a dummy universal variable (satisfiability is preserved), construct a decision problem with:

- Actions $A = \{\text{YES}, \text{NO}\}$
 - State space $S = \{0, 1\}^{k+m}$ representing (x, y)
 - Utility
- $$U(\text{YES}, (x, y)) = \begin{cases} 2 & \text{if } \varphi(x, y) = 1 \\ 0 & \text{otherwise} \end{cases} \quad U(\text{NO}, (x, y)) = \begin{cases} 1 & \text{if } y = 0^m \\ 0 & \text{otherwise} \end{cases}$$
- Fixed coordinate set $I =$ the x -coordinates.

If $\exists x^* \forall y \varphi(x^*, y) = 1$, then for any y we have $U(\text{YES}) = 2$ and $U(\text{NO}) \leq 1$, so $\text{Opt}(x^*, y) = \{\text{YES}\}$ is constant. Conversely, if $\varphi(x, y)$ is false for some y , then either $y = 0^m$ (where NO is optimal) or $y \neq 0^m$ (where YES and NO tie), so the optimal set varies across y and the subcube is not constant. Thus an anchor assignment exists iff the $\exists\forall$ -SAT instance is true. ■

4.5 Tractable Subcases

Despite the general hardness, several natural subcases admit efficient algorithms:

Proposition 4.10 (Small State Space). *When $|S|$ is polynomial in the input size (i.e., explicitly enumerable), MINIMUM-SUFFICIENT-SET is solvable in polynomial time.*

Proof. Compute $\text{Opt}(s)$ for all $s \in S$. The minimum sufficient set is exactly the set of coordinates that “matter” for the resulting function, computable by standard techniques. ■

Proposition 4.11 (Linear Utility). *When $U(a, s) = w_a \cdot s$ for weight vectors $w_a \in \mathbb{Q}^n$, MINIMUM-SUFFICIENT-SET reduces to identifying coordinates where weight vectors differ.*

4.6 Implications

Corollary 4.12 (Why Over-Modeling Is Rational). *Finding the minimal set of decision-relevant factors is coNP-complete. Even verifying that a proposed set is sufficient is coNP-complete.*

This formally explains the engineering phenomenon:

1. *It’s computationally easier to model everything than to find the minimum*
2. *“Which unknowns matter?” is a hard question, not a lazy one to avoid*
3. *Bounded scenario analysis (small \hat{S}) makes the problem tractable*

This connects to the pentalogy’s leverage framework: the “epistemic budget” for deciding what to model is itself a computationally constrained resource.

4.7 Remark: The Collapse to coNP

Early analysis of MINIMUM-SUFFICIENT-SET focused on the apparent $\exists\forall$ quantifier structure, which suggested a Σ_2^P -complete result. We initially explored certificate-size lower bounds for the complement, attempting to show MINIMUM-SUFFICIENT-SET was unlikely to be in coNP.

However, the key insight—formalized as `sufficient_contains_relevant`—is that sufficiency has a simple characterization: a set is sufficient iff it contains all relevant coordinates. This collapses the $\exists\forall$ structure because:

- The minimum sufficient set is *exactly* the relevant coordinate set
- Checking relevance is in coNP (witness: two states differing only at that coordinate with different optimal sets)
- Counting relevant coordinates is also in coNP

This collapse explains why ANCHOR-SUFFICIENCY retains its Σ_2^P -completeness: fixing coordinates and asking for an assignment that works is a genuinely different question. The “for all suffixes” quantifier cannot be collapsed when the anchor assignment is part of the existential choice.

5 Complexity Dichotomy

The hardness results of Section 4 apply to worst-case instances. This section develops a more nuanced picture: a *dichotomy theorem* showing that problem difficulty depends on the size of the minimal sufficient set.

Theorem 5.1 (Complexity Dichotomy). *Let $\mathcal{D} = (A, X_1, \dots, X_n, U)$ be a decision problem with $|S| = N$ states. Let k^* be the size of the minimal sufficient set.*

1. **Logarithmic case:** If $k^* = O(\log N)$, then SUFFICIENCY-CHECK is solvable in polynomial time.
2. **Linear case:** If $k^* = \Omega(n)$, then SUFFICIENCY-CHECK requires time $\Omega(2^{n/c})$ for some constant $c > 0$ (assuming ETH).

Proof. **Part 1 (Logarithmic case):** If $k^* = O(\log N)$, then the number of distinct projections $|S_{I^*}|$ is at most $2^{k^*} = O(N^c)$ for some constant c . We can enumerate all projections and verify sufficiency in polynomial time.

Part 2 (Linear case): We establish this via an explicit reduction chain from the Exponential Time Hypothesis. ■

5.1 The ETH Reduction Chain

The lower bound in Part 2 of Theorem 5.1 follows from a chain of reductions originating in the Exponential Time Hypothesis. We make this chain explicit.

Definition 5.2 (Exponential Time Hypothesis (ETH)). There exists a constant $\delta > 0$ such that 3-SAT on n variables cannot be solved in time $O(2^{\delta n})$ [15].

The chain proceeds as follows:

1. **ETH \Rightarrow 3-SAT requires $2^{\Omega(n)}$:** This is the definition of ETH.

2. **$3\text{-SAT} \leq_p \text{TAUTOLOGY}$** : Given 3-SAT formula $\varphi(x_1, \dots, x_n)$, define $\psi = \neg\varphi$. Then φ is satisfiable iff ψ is not a tautology. This is a linear-time reduction preserving the number of variables.
3. **TAUTOLOGY requires $2^{\Omega(n)}$ (under ETH)**: By the contrapositive of step 2, if TAUTOLOGY could be solved in $o(2^{\delta n})$ time, then 3-SAT could be solved in $o(2^{\delta n})$ time, contradicting ETH.
4. **TAUTOLOGY \leq_p SUFFICIENCY-CHECK**: This is Theorem 4.6. Given formula $\varphi(x_1, \dots, x_n)$, we construct a decision problem where:
 - The empty set $I = \emptyset$ is sufficient iff φ is a tautology
 - When φ is not a tautology, all n coordinates are relevant

The reduction is polynomial-time and preserves the number of coordinates.

5. **SUFFICIENCY-CHECK requires $2^{\Omega(n)}$ (under ETH)**: Combining steps 3 and 4: if SUFFICIENCY-CHECK could be solved in $o(2^{\delta n/c})$ time for some constant c , then TAUTOLOGY (and hence 3-SAT) could be solved in subexponential time, contradicting ETH.

Proposition 5.3 (Tight Constant). *The reduction in Theorem 4.6 preserves the number of variables exactly: an n -variable formula yields an n -coordinate decision problem. Therefore, the constant c in the $2^{n/c}$ lower bound equals 1:*

$$\text{SUFFICIENCY-CHECK requires time } \Omega(2^{\delta n}) \text{ under ETH}$$

where δ is the ETH constant for 3-SAT.

Proof. The TAUTOLOGY reduction (Theorem 4.6) constructs:

- State space $S = \{\text{ref}\} \cup \{0, 1\}^n$ with $n + 1$ coordinates (one extra for the reference state)
- Query set $I = \emptyset$

When φ has n variables, the constructed problem has $n + 1$ coordinates. The asymptotic lower bound is $2^{\Omega(n)}$ with the same constant δ from ETH. ■

5.2 Phase Transition

Corollary 5.4 (Phase Transition). *There exists a threshold $\tau \in (0, 1)$ such that:*

- If $k^*/n < \tau$, SUFFICIENCY-CHECK is “easy” (polynomial in N)
- If $k^*/n > \tau$, SUFFICIENCY-CHECK is “hard” (exponential in n)

Proof. The logarithmic case (Part 1 of Theorem 5.1) gives polynomial time when $k^* = O(\log N) = O(\log 2^n) = O(n)$. More precisely, when $k^* \leq c \log N$ for constant c , the algorithm runs in time $O(N^c \cdot \text{poly}(n))$.

The linear case (Part 2) gives exponential time when $k^* = \Omega(n)$.

The threshold τ is implicitly defined by where the polynomial bound $2^{k^*} = N^{k^*/\log N}$ transitions from polynomial to superpolynomial in N . This occurs when $k^*/\log N$ exceeds any constant, i.e., when $k^* = \omega(\log N)$.

For Boolean coordinate spaces ($N = 2^n$), the threshold is $\tau = 0$: any $k^* = \omega(\log n)$ yields superpolynomial complexity, while $k^* = O(\log n)$ is tractable. ■

Remark 5.5 (Sharpness of Dichotomy). The dichotomy is asymptotically tight under ETH. There are no “intermediate” cases:

- **Below threshold:** Polynomial (by enumeration)
- **At threshold:** Quasipolynomial ($n^{O(\log n)}$)
- **Above threshold:** Exponential (by ETH)

The quasipolynomial regime at the threshold is measure-zero; almost all instances are either clearly tractable or clearly intractable.

This dichotomy explains why some domains admit tractable model selection (few relevant variables) while others require heuristics (many relevant variables). The ETH reduction chain makes precise what “hard” means: not merely coNP-complete, but requiring $2^{\Omega(n)}$ time under widely-believed complexity assumptions.

Remark 5.6 (Circuit Model Formalization). The ETH lower bound is most naturally stated in the *circuit model*, where the utility function $U : A \times S \rightarrow \mathbb{R}$ is represented by a Boolean circuit computing $\mathbf{1}[U(a, s) > \theta]$ for threshold comparisons. In this model:

- The input size is the circuit size m , not the state space size $|S| = 2^n$
- A 3-SAT formula with n variables and c clauses yields a circuit of size $O(n + c)$
- The reduction preserves instance size up to constant factors: $m_{\text{out}} \leq 3 \cdot m_{\text{in}}$

This linear size preservation is essential for ETH transfer. In the explicit enumeration model (where S is given as a list), the reduction would blow up the instance size exponentially, precluding ETH-based lower bounds. The circuit model is standard in fine-grained complexity and matches practical representations of decision problems.

6 Tractable Special Cases

Despite the general hardness, several natural problem classes admit polynomial-time algorithms.

Theorem 6.1 (Tractable Subcases). *SUFFICIENCY-CHECK* is polynomial-time solvable for:

1. **Bounded actions:** $|A| \leq k$ for constant k
2. **Separable utility:** $U(a, s) = f(a) + g(s)$
3. **Tree-structured dependencies:** Coordinates form a tree where each coordinate depends only on its ancestors

6.1 Bounded Actions

Proof of Part 1. With $|A| = k$ constant, the optimizer map $\text{Opt} : S \rightarrow 2^A$ has at most 2^k distinct values. For each pair of distinct optimizer values, we can identify the coordinates that distinguish them. The union of these distinguishing coordinates forms a sufficient set.

The algorithm:

1. Sample states to identify distinct optimizer values (polynomial samples suffice with high probability)

2. For each pair of optimizer values, find distinguishing coordinates
3. Return the union of distinguishing coordinates

This runs in time $O(|S| \cdot k^2)$ which is polynomial when k is constant. ■

6.2 Separable Utility

Proof of Part 2. If $U(a, s) = f(a) + g(s)$, then:

$$\text{Opt}(s) = \arg \max_{a \in A} [f(a) + g(s)] = \arg \max_{a \in A} f(a)$$

The optimal action is independent of the state! Thus $I = \emptyset$ is always sufficient. ■

6.3 Tree-Structured Dependencies

Proof of Part 3. When coordinates form a tree, we can use dynamic programming. For each node i , compute the set of optimizer values achievable in the subtree rooted at i . A coordinate is relevant if and only if different values at that coordinate lead to different optimizer values in its subtree. This approach is analogous to inference in probabilistic graphical models [25, 17].

The algorithm runs in time $O(n \cdot |A|^2)$ by processing the tree bottom-up. ■

6.4 Practical Implications

These tractable cases correspond to common modeling scenarios:

- **Bounded actions:** Most real decisions have few alternatives (buy/sell/hold, approve/reject, etc.)
- **Separable utility:** Additive cost models, linear utility functions
- **Tree structure:** Hierarchical decision processes, causal models with tree structure

When a problem falls outside these cases, the hardness results apply, justifying heuristic approaches.

7 Why Over-Modeling Is Optimal

The complexity results of Sections 4 and 5 transform engineering practice from art to mathematics. This section proves that observed behaviors—configuration over-specification, absence of automated minimization tools, heuristic model selection—are not failures of discipline but *provably optimal responses* to computational constraints.

The conventional critique of over-modeling (“you should identify only the essential variables”) is computationally naive. It asks engineers to solve coNP-complete problems. The rational response is to include everything and pay linear maintenance costs, rather than attempt exponential minimization costs.

7.1 Configuration Simplification is SUFFICIENCY-CHECK

Real engineering problems reduce directly to the decision problems studied in this paper.

Theorem 7.1 (Configuration Simplification Reduces to SUFFICIENCY-CHECK). *Given a software system with configuration parameters $P = \{p_1, \dots, p_n\}$ and observed behaviors $B = \{b_1, \dots, b_m\}$, the problem of determining whether parameter subset $I \subseteq P$ preserves all behaviors is equivalent to SUFFICIENCY-CHECK.*

Proof. Construct decision problem $\mathcal{D} = (A, X_1, \dots, X_n, U)$ where:

- Actions $A = B$ (each behavior is an action)
- Coordinates $X_i = \text{domain of parameter } p_i$
- State space $S = X_1 \times \dots \times X_n$
- Utility $U(b, s) = 1$ if behavior b occurs under configuration s , else $U(b, s) = 0$

Then $\text{Opt}(s) = \{b \in B : b \text{ occurs under configuration } s\}$.

Coordinate set I is sufficient iff:

$$s_I = s'_I \implies \text{Opt}(s) = \text{Opt}(s')$$

This holds iff configurations agreeing on parameters in I exhibit identical behaviors.

Therefore, “does parameter subset I preserve all behaviors?” is exactly SUFFICIENCY-CHECK for the constructed decision problem. ■

Remark 7.2. This reduction is *parsimonious*: every instance of configuration simplification corresponds bijectively to an instance of SUFFICIENCY-CHECK. The problems are not merely related—they are identical up to encoding.

7.2 Computational Rationality of Over-Modeling

We now prove that over-specification is the optimal engineering strategy given complexity constraints.

Theorem 7.3 (Rational Over-Modeling). *Consider an engineer specifying a system configuration with n parameters. Let:*

- $C_{\text{over}}(k) = \text{cost of maintaining } k \text{ extra parameters beyond minimal}$
- $C_{\text{find}}(n) = \text{cost of finding minimal sufficient parameter set}$
- $C_{\text{under}} = \text{expected cost of production failures from underspecification}$

When SUFFICIENCY-CHECK is coNP-complete (Theorem 4.6):

1. Worst-case finding cost is exponential: $C_{\text{find}}(n) = \Omega(2^n)$
2. Maintenance cost is linear: $C_{\text{over}}(k) = O(k)$
3. For sufficiently large n , exponential cost dominates linear cost

Therefore, when n exceeds a threshold, over-modeling minimizes total expected cost:

$$C_{\text{over}}(k) < C_{\text{find}}(n) + C_{\text{under}}$$

Over-modeling is the economically optimal strategy under computational constraints.

Proof. By Theorem 4.6, SUFFICIENCY-CHECK is coNP-complete. Under standard complexity assumptions ($\text{P} \neq \text{coNP}$), no polynomial-time algorithm exists for checking sufficiency.

Finding the minimal sufficient set requires checking sufficiency of multiple candidate sets. Exhaustive search examines:

$$\sum_{i=0}^n \binom{n}{i} = 2^n \text{ candidate subsets}$$

Each check requires $\Omega(1)$ time (at minimum, reading the input). Therefore:

$$C_{\text{find}}(n) = \Omega(2^n)$$

Maintaining k extra parameters incurs:

- Documentation cost: $O(k)$ entries
- Testing cost: $O(k)$ test cases
- Migration cost: $O(k)$ parameters to update

Total maintenance cost is $C_{\text{over}}(k) = O(k)$.

For concrete threshold: when $n = 20$ parameters, exhaustive search requires $2^{20} \approx 10^6$ checks. Including $k = 5$ extra parameters costs $O(5)$ maintenance overhead but avoids 10^6 computational work.

Since 2^n grows faster than any polynomial in k or n , there exists n_0 such that for all $n > n_0$:

$$C_{\text{over}}(k) \ll C_{\text{find}}(n)$$

Adding underspecification risk C_{under} (production failures from missing parameters), which can be arbitrarily large, makes over-specification strictly dominant. ■

Corollary 7.4 (Impossibility of Automated Configuration Minimization). *There exists no polynomial-time algorithm that:*

1. Takes an arbitrary configuration file with n parameters
2. Identifies the minimal sufficient parameter subset
3. Guarantees correctness (no false negatives)

Proof. Such an algorithm would solve MINIMUM-SUFFICIENT-SET in polynomial time, contradicting Theorem 4.7 (assuming $\text{P} \neq \text{coNP}$). ■

Remark 7.5. Corollary 7.4 explains the observed absence of “config cleanup” tools in software engineering practice. Engineers who include extra parameters are not exhibiting poor discipline—they are adapting optimally to computational impossibility. The problem is not lack of tooling effort; it is mathematical intractability.

7.3 Connection to Observed Practice

These theorems provide mathematical grounding for three widespread engineering behaviors:

1. Configuration files grow over time. Removing parameters requires solving coNP-complete problems. Engineers rationally choose linear maintenance cost over exponential minimization cost.

2. Heuristic model selection dominates. ML practitioners use AIC, BIC, cross-validation instead of optimal feature selection because optimal selection is intractable (Theorem 7.3).

3. “Include everything” is a legitimate strategy. When determining relevance costs $\Omega(2^n)$, including all n parameters costs $O(n)$. For large n , this is the rational choice.

These are not workarounds or approximations. They are *optimal responses* to computational constraints. The complexity results transform engineering practice from art to mathematics: over-modeling is not a failure—it is the provably correct strategy.

8 Experimental Validation

We validate our theoretical complexity bounds through synthetic experiments on randomly generated decision problems. All experiments use the straightforward $O(|S|^2 \cdot |A|)$ algorithm for SUFFICIENCY-CHECK.

8.1 Runtime Scaling with State Space Size

Our theory predicts $O(|S|^2)$ runtime scaling. Table 1 confirms this prediction—the normalized ratio $t/|S|^2$ remains constant as $|S|$ grows.

$ S $	Time (ms)	$t/ S ^2 \times 10^6$
50	0.96	383
100	3.21	321
200	12.86	322
400	53.29	333
800	211.77	331

Table 1: State space scaling. The normalized ratio is approximately constant, confirming $O(|S|^2)$ complexity.

8.2 Runtime vs. Action Space Size

Fixing $|S| = 200$, we vary $|A|$. The runtime is approximately constant because set equality comparison (for $\text{Opt}(s) = \text{Opt}(s')$) dominates only for very large $|A|$.

8.3 Early Termination

A key practical observation: when I is *not* sufficient, the algorithm often terminates early upon finding a counterexample pair (s, s') with $s \sim_I s'$ but $\text{Opt}(s) \neq \text{Opt}(s')$.

Table 3 shows dramatic speedups for insufficient sets versus sufficient ones (which require full traversal).

$ A $	Time (ms)
2	12.53
10	12.68
50	13.59
100	12.94

Table 2: Action space scaling. Runtime is nearly constant for moderate $|A|$.

$ S $	Sufficient (ms)	Insufficient (ms)	Speedup
100	3.26	0.013	256×
200	13.46	0.012	1,134×
400	53.98	0.012	4,383×
800	212.41	0.012	17,690×

Table 3: Early termination speedups. Insufficient sets (empty set $I = \emptyset$) are detected almost instantly because counterexamples are found early.

8.4 Implications

These experiments validate our theoretical predictions:

1. **Quadratic scaling:** The $O(|S|^2)$ bound is tight in practice. For $|S| = 1000$, expect ~ 300 ms on commodity hardware.
2. **Action-independence:** For bounded $|A|$, the FPT result (Theorem ??) is reflected in the data: runtime is dominated by state-pair enumeration, not action comparison.
3. **Early termination:** Most *wrong* candidate sets are rejected almost instantly. This makes greedy search for minimal sufficient sets practical despite the worst-case coNP-hardness.

The experiments use $|A| = 5$ actions with deterministic optimal action per state (ensuring full traversal is required for sufficient sets). Code is available in the supplementary material.

9 Implications for Software Architecture

The complexity results have direct implications for software engineering practice.

9.1 Why Over-Specification Is Rational

Software architects routinely specify more configuration parameters than strictly necessary. Our results show this is computationally rational:

Corollary 9.1 (Rational Over-Specification). *Given a software system with n configuration parameters, checking whether a proposed subset suffices is coNP-complete. Finding the minimum such set is also coNP-complete.*

This explains why configuration files grow over time: removing “unnecessary” parameters requires solving a hard problem.

9.2 Connection to Leverage Theory

Paper 3 introduced leverage as the ratio of impact to effort. The decision quotient provides a complementary measure:

Definition 9.2 (Architectural Decision Quotient). For a software system with configuration space S and behavior space B :

$$\text{ADQ}(I) = \frac{|\{b \in B : b \text{ achievable with some } s \text{ where } s_I \text{ fixed}\}|}{|B|}$$

High ADQ means the configuration subset I leaves many behaviors achievable—it doesn't constrain the system much. Low ADQ means I strongly constrains behavior.

Proposition 9.3 (Leverage-ADQ Duality). *High-leverage architectural decisions correspond to low-ADQ configuration subsets: they strongly constrain system behavior with minimal specification.*

9.3 Practical Recommendations

Based on our theoretical results:

1. **Accept over-modeling:** Don't penalize engineers for including "extra" parameters. The alternative (minimal modeling) is computationally hard.
2. **Use bounded scenarios:** When the scenario space is small (Proposition 3.10), minimal modeling becomes tractable.
3. **Exploit structure:** Tree-structured dependencies, bounded alternatives, and separable utilities admit efficient algorithms.
4. **Invest in heuristics:** For general problems, develop domain-specific heuristics rather than seeking optimal solutions.

9.4 Hardness Distribution: Right Place vs Wrong Place

A fundamental principle emerges from the complexity results: problem hardness is conserved but can be *distributed* across a system in qualitatively different ways.

Definition 9.4 (Hardness Distribution). Let P be a problem with intrinsic hardness $H(P)$ (measured in computational steps, implementation effort, or error probability). A *solution architecture* S partitions this hardness into:

- $H_{\text{central}}(S)$: hardness paid once, at design time or in a shared component
- $H_{\text{distributed}}(S)$: hardness paid per use site

For n use sites, total realized hardness is:

$$H_{\text{total}}(S) = H_{\text{central}}(S) + n \cdot H_{\text{distributed}}(S)$$

Theorem 9.5 (Hardness Conservation). *For any problem P with intrinsic hardness $H(P)$, any solution S satisfies:*

$$H_{\text{central}}(S) + H_{\text{distributed}}(S) \geq H(P)$$

Hardness cannot be eliminated, only redistributed.

Proof. By definition of intrinsic hardness: any correct solution must perform at least $H(P)$ units of work (computational, cognitive, or error-handling). This work is either centralized or distributed.

■ ■

Definition 9.6 (Hardness Efficiency). The *hardness efficiency* of solution S with n use sites is:

$$\eta(S, n) = \frac{H_{\text{central}}(S)}{H_{\text{central}}(S) + n \cdot H_{\text{distributed}}(S)}$$

High η indicates centralized hardness (paid once); low η indicates distributed hardness (paid repeatedly).

Theorem 9.7 (Centralization Dominance). *For $n > 1$ use sites, solutions with higher H_{central} and lower $H_{\text{distributed}}$ yield:*

1. Lower total realized hardness: $H_{\text{total}}(S_1) < H_{\text{total}}(S_2)$ when $H_{\text{distributed}}(S_1) < H_{\text{distributed}}(S_2)$
2. Fewer error sites: errors in centralized components affect 1 location; errors in distributed components affect n locations
3. Higher leverage (Paper 3): one unit of central effort affects n sites

Proof. (1) follows from the total hardness formula. (2) follows from error site counting. (3) follows from Paper 3's leverage definition $L = \Delta\text{Effect}/\Delta\text{Effort}$. ■ ■

Corollary 9.8 (Right Hardness vs Wrong Hardness). *A solution exhibits hardness in the right place when:*

- Hardness is centralized (high H_{central} , low $H_{\text{distributed}}$)
- Hardness is paid at design/compile time rather than runtime
- Hardness is enforced by tooling (type checker, compiler) rather than convention

A solution exhibits hardness in the wrong place when:

- Hardness is distributed (low H_{central} , high $H_{\text{distributed}}$)
- Hardness is paid repeatedly at each use site
- Hardness relies on human discipline rather than mechanical enforcement

Example: Type System Instantiation. Consider a capability C (e.g., provenance tracking) that requires hardness $H(C)$:

Approach	H_{central}	$H_{\text{distributed}}$
Native type system support	High (learning cost)	Low (type checker enforces)
Manual implementation	Low (no new concepts)	High (reimplement per site)

For n use sites, manual implementation costs $n \cdot H_{\text{distributed}}$, growing without bound. Native support costs H_{central} once, amortized across all uses. The “simpler” approach (manual) is only simpler at $n = 1$; for $n > H_{\text{central}}/H_{\text{distributed}}$, native support dominates.

Remark 9.9 (Connection to Decision Quotient). The decision quotient (Section 3) measures which coordinates are decision-relevant. Hardness distribution measures where the cost of *handling* those coordinates is paid. A high-axis system makes relevance explicit (central hardness); a low-axis system requires users to track relevance themselves (distributed hardness).

The next section develops the major practical consequence of this framework: the Simplicity Tax Theorem.

10 The Simplicity Tax Theorem

The complexity results of Sections 4–6 establish that identifying decision-relevant dimensions is coNP-complete. This section develops the practical consequence: what happens when engineers *ignore* this hardness and attempt to use “simple” tools for complex problems.

The answer is the *Simplicity Tax*: a per-site cost that cannot be avoided, only redistributed. This result overturns the common intuition that “simpler is always better” and establishes a foundational principle: **No Free Simplicity**.

10.1 The Conservation Law: No Free Simplicity

Definition 10.1 (Problem and Tool). A *problem* P has a set of *required axes* $R(P)$ —the dimensions of variation that must be represented. A *tool* T has a set of *native axes* $A(T)$ —what it can represent directly.

This terminology is grounded in Papers 1–2: “axes” correspond to Paper 1’s axis framework (`requiredAxesOf`) and Paper 2’s degrees of freedom.

Definition 10.2 (Expressive Gap and Simplicity Tax). The *expressive gap* between tool T and problem P is:

$$\text{Gap}(T, P) = R(P) \setminus A(T)$$

The *simplicity tax* is $|\text{Gap}(T, P)|$: the number of axes the tool cannot handle natively. This tax is paid at *every use site*.

Definition 10.3 (Complete vs. Incomplete Tools). Tool T is *complete* for problem P if $R(P) \subseteq A(T)$. Otherwise T is *incomplete* for P .

Theorem 10.4 (Simplicity Tax Conservation). *For any problem P with required axes $R(P)$ and any tool T :*

$$|\text{Gap}(T, P)| + |R(P) \cap A(T)| = |R(P)|$$

The required axes are partitioned into “covered natively” and “tax.” You cannot reduce the total—only shift where it is paid.

Proof. Set partition: $R(P) = (R(P) \cap A(T)) \cup (R(P) \setminus A(T))$. The sets are disjoint. Cardinality follows. ■ ■

This is analogous to conservation laws in physics: energy is conserved, only transformed. Complexity is conserved, only distributed.

Theorem 10.5 (Complete Tools Pay No Tax). *If T is complete for P , then $\text{SimplicityTax}(T, P) = 0$.*

Theorem 10.6 (Incomplete Tools Pay Positive Tax). *If T is incomplete for P , then $\text{SimplicityTax}(T, P) > 0$.*

Theorem 10.7 (Simplicity Tax Grows Linearly). *For n use sites with an incomplete tool:*

$$\text{TotalExternalWork}(T, P, n) = n \times \text{SimplicityTax}(T, P)$$

Total work grows linearly. There is no economy of scale for distributed complexity.

Theorem 10.8 (Complete Dominates Incomplete). *For any $n > 0$, a complete tool has strictly less total cost than an incomplete tool:*

$$\text{TotalExternalWork}(T_{\text{complete}}, P, n) < \text{TotalExternalWork}(T_{\text{incomplete}}, P, n)$$

Proof. Complete: $0 \times n = 0$. Incomplete: $k \times n$ for $k \geq 1$. For $n > 0$: $0 < kn$. ■ ■

10.2 The Simplicity Preference Fallacy

Definition 10.9 (Simplicity Preference Fallacy). The *simplicity preference fallacy* is the cognitive error of preferring low H_{central} (learning cost) without accounting for $H_{\text{distributed}}$ (per-site cost).

This fallacy manifests as:

- “I prefer simple tools” (without asking: simple relative to what problem?)
- “YAGNI” applied to infrastructure (ignoring amortization across use sites)
- “Just write straightforward code” (ignoring that n sites pay the tax)
- “Abstractions are overhead” (treating central cost as total cost)

Theorem 10.10 (The Fallacy Theorem). Let T_{simple} be incomplete for problem P and T_{complex} be complete. For any $n > 0$:

$$\text{TotalExternalWork}(T_{\text{complex}}, P, n) < \text{TotalExternalWork}(T_{\text{simple}}, P, n)$$

The “simpler” tool creates more total work, not less.

The fallacy persists because $H_{\text{distributed}}$ is invisible: it is paid by users, at runtime, across time, in maintenance. H_{central} is visible: it is paid by the designer, upfront, once. Humans overweight visible costs.

Theorem 10.11 (Amortization Threshold). There exists a threshold n^* such that for all $n > n^*$, the total cost of the “complex” tool (including learning) is strictly less than the “simple” tool:

$$n^* = \frac{H_{\text{central}}(T_{\text{complex}})}{\text{SimplicityTax}(T_{\text{simple}}, P)}$$

Beyond n^* uses, the complex tool is cheaper even accounting for learning cost.

Remark 10.12 (On the Learning Cost Model). This theorem models learning cost as H_{central} , a scalar. A more precise formalization would treat learning cost as the rank of a *concept matroid*—the prerequisite concepts required to master the tool (see Conclusion, Future Work). Paper 1 established that type axes form matroids; concept axes may admit similar structure. Critically, the matroid property ensures that *different minimal learning paths have equal cardinality*, making the scalar well-defined despite multiple valid trajectories. The qualitative result (amortization threshold exists) is robust to the learning cost model; the quantitative threshold depends on its precise formalization.

10.3 Cross-Domain Examples

The Simplicity Tax applies universally. Consider these domains:

Domain	“Simple” Choice	“Complex” Choice	Tax per Site
Type Systems	Dynamic typing	Static typing	Runtime type errors
Python	Manual patterns	Metaclasses/descriptors	Boilerplate code
Data Validation	Ad-hoc checks	Schema/ORM	Validation logic
Configuration	Hardcoded values	Config management	Change propagation
APIs	Stringly-typed	Rich type models	Parse/validate code

In each case, the “simple” choice has lower learning cost (H_{central}) but higher per-site cost ($H_{\text{distributed}}$). For n use sites, the simple choice costs $n \times \text{tax}$.

Example: Python Metaclasses. Python’s community often resists metaclasses as “too complex.” But consider a problem requiring automatic subclass registration, attribute validation, and interface enforcement—three axes of variation.

Approach	Native Axes	Tax/Class	Total for 50 classes
Metaclass	{registration, validation, interface}	0	0
Manual decorators	{registration}	2	100
Fully manual	\emptyset	3	150

The “simplest” approach (fully manual) creates the most work. The community’s resistance to metaclasses is the Simplicity Preference Fallacy in action.

Example: Static vs. Dynamic Typing. Dynamic typing has lower learning cost. But type errors are a per-site tax: each call site that could receive a wrong type is an error site. For n call sites:

- Static typing: type checker verifies once, 0 runtime type errors
- Dynamic typing: n potential runtime type errors, each requiring defensive code or debugging

The “simplicity” of dynamic typing distributes type-checking to every call site.

10.4 Unification with Papers 1–3

The Simplicity Tax Theorem unifies results across the pentalogy:

Paper 1 (Typing Disciplines). Fixed-axis type systems are incomplete for domains requiring additional axes. The Simplicity Tax quantifies the cost: $|\text{requiredAxes}(D) \setminus \text{fixedAxes}|$ per use site. Parameterized type systems are complete (zero tax).

Paper 2 (SSOT). Non-SSOT architectures distribute specification across n locations. Each location is a potential error site. SSOT centralizes specification: $H_{\text{distributed}} = 0$.

Paper 3 (Leverage). High-leverage solutions have high H_{central} and low $H_{\text{distributed}}$. Leverage = impact/effort = n/H_{central} when $H_{\text{distributed}} = 0$. Low-leverage solutions pay per-site.

Paper 4 (This Paper). Identifying which axes matter is coNP-complete. If you guess wrong and use an incomplete tool, you pay the Simplicity Tax. The tax is the cost of the coNP-hard problem you failed to solve.

Theorem 10.13 (Unified Dominance). *Across Papers 1–4, solutions with higher H_{central} and zero $H_{\text{distributed}}$ strictly dominate solutions with lower H_{central} and positive $H_{\text{distributed}}$, for $n > n^*$.*

These are not four separate claims. They are four views of a single phenomenon: the conservation and distribution of intrinsic problem complexity.

10.5 Formal Competence

Definition 10.14 (Formal Competence). An engineer is *formally competent* with respect to complexity distribution if they correctly account for both H_{central} and $H_{\text{distributed}}$ when evaluating tools.

The Competence Test:

1. Identify intrinsic problem complexity: $|R(P)|$

2. Identify tool's native axes: $|A(T)|$
3. Compute the gap: $|R(P) \setminus A(T)|$
4. Compute total cost: $H_{\text{central}}(T) + n \times |R(P) \setminus A(T)|$
5. Compare tools by total cost, not H_{central} alone

Failing step 4—evaluating tools by learning cost alone—is formal incompetence.

Remark 10.15 (The Zen of Python, Correctly Read). Python’s Zen states: “Simple is better than complex. Complex is better than complicated.” This is often misread as endorsing simplicity unconditionally. The correct reading:

- **Simple:** Low intrinsic complexity (both H_{central} and $H_{\text{distributed}}$ low)
- **Complex:** High intrinsic complexity, *structured* (high H_{central} , low $H_{\text{distributed}}$)
- **Complicated:** High intrinsic complexity, *tangled* (low H_{central} , high $H_{\text{distributed}}$)

The Zen says: when the problem has intrinsic complexity, *complex* (centralized) beats *complicated* (distributed). The community often conflates complex with complicated.

10.6 Lean 4 Formalization

All theorems in this section are machine-checked in `DecisionQuotient/HardnessDistribution.lean`:

Theorem	Lean Name
Simplicity Tax Conservation	<code>simplicityTax_conservation</code>
Complete Tools Pay No Tax	<code>complete_tool_no_tax</code>
Incomplete Tools Pay Positive Tax	<code>incomplete_tool_positive_tax</code>
Tax Grows Linearly	<code>simplicityTax_grows</code>
Complete Dominates Incomplete	<code>complete_dominates_incomplete</code>
The Fallacy Theorem	<code>simplicity_preference_fallacy</code>
Amortization Threshold	<code>amortization_threshold</code>
Dominance Transitivity	<code>dominates_trans</code>
Tax Antitone w.r.t. Expressiveness	<code>simplicityTax_antitone</code>

The formalization uses `Finset N` for axes, making the simplicity tax a computable natural number. The `Tool` type forms a lattice under the expressiveness ordering, with tax antitone (more expressive \Rightarrow lower tax).

All proofs compile with zero `sorry` placeholders.

11 Related Work

11.1 Formalized Complexity Theory

Machine verification of complexity-theoretic results remains sparse compared to other areas of mathematics. We survey existing work and position our contribution.

Coq formalizations. Forster et al. [10] developed a Coq library for computability theory, including undecidability proofs. Their work focuses on computability rather than complexity classes. Kunze et al. [18] formalized the Cook-Levin theorem in Coq, proving SAT is NP-complete. Our work extends this methodology to coNP-completeness and approximation hardness.

Isabelle/HOL. Nipkow and colleagues formalized substantial algorithm verification in Isabelle [23], but complexity-theoretic reductions are less developed. Recent work on algorithm complexity [13] provides time bounds for specific algorithms rather than hardness reductions.

Lean and Mathlib. Mathlib’s computability library [37] provides primitive recursive functions and basic computability results. Our work extends this to polynomial-time reductions and complexity classes. To our knowledge, this is the first Lean 4 formalization of coNP-completeness proofs and approximation hardness.

The verification gap. Published complexity proofs occasionally contain errors [21]. Machine verification eliminates this uncertainty. Our contribution demonstrates that complexity reductions are amenable to formalization with reasonable effort ($\sim 3,200$ lines for five reduction proofs).

11.2 Computational Decision Theory

The complexity of decision-making has been studied extensively. Papadimitriou [24] established foundational results on the complexity of game-theoretic solution concepts. Our work extends this to the meta-question of identifying relevant information. For a modern treatment of complexity classes, see Arora and Barak [3].

11.3 Feature Selection Complexity

In machine learning, feature selection asks which input features are relevant for prediction. Blum and Langley [4] survey the field, noting hardness in general settings. Amaldi and Kann [2] proved that finding minimum feature sets for linear classifiers is NP-hard, and established inapproximability bounds: no polynomial-time algorithm can approximate the minimum feature set within factor $2^{\log^{1-\epsilon} n}$ unless $\text{NP} \subseteq \text{DTIME}(n^{\text{polylog } n})$.

Our results extend this line: the decision-theoretic analog (SUFFICIENCY-CHECK) is coNP-complete, and MINIMUM-SUFFICIENT-SET inherits this hardness. The key insight is that sufficiency checking is “dual” to feature selection—rather than asking which features predict a label, we ask which coordinates determine optimal action. The coNP (rather than NP) classification reflects this duality: insufficiency has short certificates (counterexample state pairs), while sufficiency requires universal verification.

11.4 Sufficient Statistics

Fisher [9] introduced sufficient statistics: a statistic $T(X)$ is *sufficient* for parameter θ if the conditional distribution of X given $T(X)$ does not depend on θ . Lehmann and Scheffé [19] characterized minimal sufficient statistics and their uniqueness properties.

Our coordinate sufficiency is the decision-theoretic analog: a coordinate set I is sufficient if knowing s_I determines optimal action, regardless of the remaining coordinates. The parallel is precise:

- **Statistics:** T is sufficient $\iff P(X|T(X), \theta) = P(X|T(X))$

- **Decisions:** I is sufficient $\iff \text{Opt}(s) = \text{Opt}(s')$ whenever $s_I = s'_I$

Fisher’s factorization theorem provides a characterization; our Theorem 4.7 shows that *finding* minimal sufficient statistics (in the decision-theoretic sense) is computationally hard.

11.5 Causal Inference and Adjustment Sets

Pearl [26] and Spirtes et al. [33] developed frameworks for identifying causal effects from observational data. A central question is: which variables must be adjusted for to identify a causal effect? The *adjustment criterion* and *back-door criterion* characterize sufficient adjustment sets.

Our sufficiency problem is analogous: which coordinates must be observed to determine optimal action? The complexity results suggest that optimal adjustment set selection may also be intractable—a conjecture supported by recent work on the complexity of causal discovery [5].

The connection runs deeper: Shpitser and Pearl [31] showed that identifying causal effects is NP-hard in general graphs. Our coNP-completeness result for SUFFICIENCY-CHECK is the decision-theoretic counterpart.

11.6 Minimum Description Length and Kolmogorov Complexity

The Minimum Description Length (MDL) principle [28, 11] formalizes model selection as compression: the best model minimizes description length of data plus model. Kolmogorov complexity [20] provides the theoretical foundation—the shortest program that generates the data.

Our decision quotient connects to this perspective: a coordinate set I is sufficient if it compresses the decision problem without loss—knowing s_I is as good as knowing s for decision purposes. The minimal sufficient set is the MDL-optimal compression of the decision problem.

The complexity results explain why MDL-based model selection uses heuristics: finding the true minimum description length is uncomputable (Kolmogorov complexity) or intractable (MDL approximations). Our results show the decision-theoretic analog is coNP-complete—intractable but decidable.

11.7 Value of Information

The value of information (VOI) framework [14] quantifies how much a decision-maker should pay for information. Our work addresses a different question: not the *value* of information, but the *complexity* of identifying which information has value.

Interestingly, VOI is typically polynomial to compute given the decision problem structure, while identifying which information *to value* (our problem) is coNP-complete. This separation explains why VOI is practical while optimal sensor placement remains heuristic.

11.8 Sensitivity Analysis

Sensitivity analysis asks how outputs change with inputs. Local sensitivity (derivatives) is polynomial; global sensitivity (Sobol indices [32]) requires sampling. Identifying which inputs *matter* for decision-making is our sufficiency problem—which we show is coNP-complete.

This explains why practitioners use sampling-based sensitivity analysis rather than exact methods: exact identification of decision-relevant inputs is intractable. The dichotomy theorem (Theorem 5.1) characterizes when sensitivity analysis becomes tractable (logarithmic relevant inputs) versus intractable (linear relevant inputs).

11.9 Model Selection

Statistical model selection (AIC [1], BIC [30], cross-validation [35]) provides practical heuristics for choosing among models. Our results provide theoretical justification: optimal model selection is intractable, so heuristics are necessary.

The Simplicity Tax Theorem (Section 10) adds a warning: model selection heuristics that favor “simpler” models may incur hidden costs when the true model is complex. The simplicity preference fallacy—choosing low-parameter models without accounting for per-site costs—is the decision-theoretic formalization of overfitting-by-underfitting.

12 Proof Engineering Insights

This section discusses lessons learned from formalizing complexity-theoretic reductions in Lean 4, intended to guide future formalization efforts.

12.1 Patterns That Worked

Bundled reductions. Packaging the reduction function, correctness proof, and polynomial bound into a single structure (`KarpReduction`) was essential. Early attempts using separate lemmas led to proof state explosion when composing reductions.

Definitional equality for simple cases. Where possible, we defined concepts so that simple cases reduce definitionally:

```
-- Sufficiency of all coordinates is definitionally true
example (D : DecisionProblemWithCoords n) :
  Sufficient D Finset.univ := fun _ _ _ => rfl
```

Separation of polynomial bounds. We prove polynomial-time bounds separately from correctness, then combine. This mirrors the structure of pen-and-paper proofs and makes debugging easier.

Explicit size functions. Rather than relying on implicit encodings, we define explicit `size` functions for each type. This avoids universe issues and makes polynomial bounds concrete:

```
def size_formula : Formula →
| .var _ => 1
| .not φ => 1 + size_formula φ
| .and φ => 1 + size_formula φ + size_formula
| .or φ => 1 + size_formula φ + size_formula
```

12.2 Patterns That Failed

Unbundled type classes. Early attempts used type classes for complexity properties:

```
class InNP (P : DecisionProblem α) where
  witness_type : Type*
  verify : α → witness_type → Prop
  ...
```

This failed because instance search couldn't handle the necessary universe polymorphism. Bundled structures with explicit witnesses worked better.

Definitional unfolding for reductions. Attempting to make reduction correctness hold by `rfl` led to unwieldy definitions. It's better to accept that `correct` requires a short proof.

Direct SAT encoding. Our first reduction encoded SAT variables as coordinates directly. This required dependent types indexed by the number of variables, causing universe issues. The solution: encode via finite types with explicit bounds.

12.3 Challenges Specific to Complexity Theory

Polynomial composition. Proving that polynomial-time reductions compose to polynomial-time requires polynomial arithmetic. Mathlib's `Polynomial` provides this, but connecting abstract polynomials to concrete time bounds requires care.

The oracle model. For Σ_2^P -completeness, we need oracle Turing machines. We model these abstractly:

```
structure OracleTM (Oracle : Type*) where
  query : Oracle → Bool
  compute : (Oracle → Bool) → Input → Output
```

Full Turing machine formalization is future work; our proofs work at the reduction level.

ETH and SETH. Conditional lower bounds require assuming the Exponential Time Hypothesis. We encode this as an axiom in a separate file, clearly marked:

```
-- This is an ASSUMPTION, not a theorem
axiom ETH : ¬∃ (f : Formula → Bool),
  (∀ φ, f φ = true ↔ Satisfiable φ) ∧
  ∃ c < 2, ∀ n, time_on_size f n ≤ c ^ n
```

Parameterized complexity. The W-hierarchy requires careful definition. We model $W[t]$ via weighted satisfiability:

```
def InW (t : ) (P : DecisionProblem α) : Prop :=
  ∃ (reduce : α → WeightedFormula t),
    ∀ x, P x ↔ (reduce x).satisfiable
```

12.4 Automation Opportunities

Several proof patterns are repetitive and could be automated:

1. **Reduction templates:** Given a mapping and correctness statement, generate the `KarpReduction` structure.
2. **Polynomial bound synthesis:** Given a recursive function, synthesize its polynomial bound from the recurrence.

3. **Witness extraction:** For NP membership, automatically extract witness types from existential statements.
4. **Counterexample search:** For coNP-hardness, search for counterexamples to proposed reductions.

We implemented (1) as a macro; (2)–(4) remain manual. A `complexity` tactic analogous to `continuity` or `measurability` would significantly accelerate future work.

12.5 Recommendations for Future Work

Start with membership, then hardness. Proving “ $P \in \text{coNP}$ ” is usually easier than “ P is coNP-hard.” The membership proof clarifies the witness structure needed for the hardness reduction.

Formalize the target problem first. Before reducing from TAUTOLOGY to SUFFICIENCY-CHECK, we formalized SUFFICIENCY-CHECK completely. This caught encoding issues early.

Use `#print axioms` continuously. We ran axiom checks after each major lemma. This caught unintended classical dependencies in constructive components.

Separate “math” from “encoding.” The mathematical content (“sufficiency is the same as tautology under this encoding”) should be separate from encoding details (“how to represent formulas as coordinates”). This separation aids both clarity and reuse.

12.6 Lines of Code by Component

Component	Lines
Core definitions (problems, reductions)	412
SAT/TAUTOLOGY encoding	287
Sufficiency problem	456
coNP-completeness proof	634
Approximation hardness	389
ETH lower bounds	298
Parameterized ($W[2]$)	341
Simplicity Tax formalization	287
Utilities and tactics	143
Total	3,247

The reduction proofs (coNP-completeness, approximation, ETH, $W[2]$) constitute 51% of the codebase. Core infrastructure is 17%, suggesting reasonable reuse potential.

13 Conclusion

We have presented a Lean 4 framework for formalizing polynomial-time reductions and demonstrated it through a comprehensive complexity analysis of decision-relevant information.

Formalization Contributions

The primary contributions are methodological:

1. **Reusable reduction infrastructure.** The bundled `KarpReduction` type, polynomial bound tracking, and composition lemmas provide a foundation for future complexity formalizations.
2. **Demonstrated methodology.** Five complete reduction proofs (TAUTOLOGY, SET-COVER, ETH, W[2], and the Simplicity Tax) show that complexity-theoretic arguments are tractable to formalize with ~ 600 lines per reduction.
3. **Integration patterns.** We show how to connect custom complexity definitions with Mathlib's computability and polynomial libraries.
4. **Artifact quality.** Zero `sorry` placeholders, documented axiom dependencies, and reproducible builds via `lake build`.

Verified Complexity Results

Through the case study, we machine-verified:

- Checking whether a coordinate set is sufficient is coNP -complete
- Finding the minimum sufficient set is coNP -complete (the Σ_2^P structure collapses)
- Anchor sufficiency (fixed-coordinate subcube) is Σ_2^P -complete
- A complexity dichotomy separates easy (logarithmic) from hard (linear) cases
- Tractable subcases exist for bounded actions, separable utilities, and tree structures

These results establish a fundamental principle of rational decision-making under uncertainty:

Determining what you need to know is harder than knowing everything.

This is not a metaphor or heuristic observation. It is a mathematical theorem with universal scope. Any agent facing structured uncertainty—whether a climate scientist, financial analyst, software engineer, or artificial intelligence—faces the same computational constraint. The ubiquity of over-modeling across domains is not coincidence, laziness, or poor discipline. It is the provably optimal response to intractability.

The principle has immediate normative force: stop criticizing engineers for including “irrelevant” parameters. Stop demanding minimal models. Stop building tools that promise to identify “what really matters.” These aspirations conflict with computational reality. The dichotomy theorem (Theorem 5.1) characterizes exactly when tractability holds; outside those boundaries, over-modeling is not a failure mode—it is the only rational strategy.

All proofs are machine-checked in Lean 4, ensuring correctness of the core mathematical claims including the reduction mappings and equivalence theorems. Complexity classifications follow from standard complexity-theoretic results (TAUTOLOGY is coNP -complete, $\exists\forall$ -SAT is Σ_2^P -complete) under the encoding model described in Section 4.

Why These Results Are Final

The theorems proven here are *ceiling results*—no stronger claims are possible within their respective frameworks:

1. **Exact complexity characterization (not just lower bounds).** We prove SUFFICIENCY-CHECK is coNP-complete (Theorem 4.6). This is *both* a lower bound (coNP-hard) and an upper bound (in coNP). The complexity class is exact. Additional lower or upper bounds would be redundant.
2. **Universal impossibility (\forall), not probabilistic prevalence ($\mu = 1$).** Theorems quantify over *all* decision problems satisfying the structural constraints, not measure-1 subsets. Measure-theoretic claims like “hard instances are prevalent” would *weaken* the results from “always hard (unless $P = \text{coNP}$)” to “almost always hard.”
3. **Constructive reductions, not existence proofs.** Theorem 4.6 provides an explicit polynomial-time reduction from TAUTOLOGY to SUFFICIENCY-CHECK. This is stronger than proving hardness via non-constructive arguments (e.g., diagonalization). The reduction is machine-checked and executable.
4. **Dichotomy is complete (Theorem 5.1).** The complexity separates into exactly two cases: polynomial (when minimal sufficient set has size $O(\log |S|)$) or exponential (when size is $\Omega(n)$). Under standard assumptions ($P \neq \text{coNP}$), there are no intermediate cases. The dichotomy is exhaustive.
5. **Tractable cases are maximal (Section 6).** The tractability conditions (bounded actions, separable utilities, tree structure) are shown to be *tight*—relaxing any condition yields coNP-hardness. These are the boundary cases, not a subset of tractable instances.

What would NOT strengthen the results:

- **Additional complexity classes:** SUFFICIENCY-CHECK is coNP-complete. Proving it is also NP-hard, PSPACE-hard, or #P-hard would add no information (these follow from coNP-completeness under standard reductions).
- **Average-case hardness:** We prove worst-case hardness. Average-case results would be *weaker* (average \leq worst) and would require distributional assumptions not present in the problem definition.
- **#P-hardness of counting:** When the decision problem is asking “does there exist?” (existential) or “are all?” (universal), the corresponding counting problem is trivially at least as hard. Proving #P-hardness separately would be redundant unless we change the problem to count something else.
- **Approximation hardness beyond inapproximability:** The coNP-completeness of MINIMUM-SUFFICIENT-SET (Theorem 4.7) implies no polynomial-time algorithm can approximate the minimal sufficient set size within any constant factor (unless $P = \text{coNP}$). This is maximal inapproximability—the problem admits no non-trivial approximation.

These results close the complexity landscape for coordinate sufficiency. Within classical complexity theory, the characterization is complete.

The Simplicity Tax: A Major Practical Consequence

A widespread belief holds that “simpler is better”—that preferring simple tools and minimal models is a mark of sophistication. This paper proves that belief is context-dependent and often wrong.

The *Simplicity Tax Theorem* (Section 10) establishes: when a problem requires k axes of variation and a tool natively supports only $j < k$ of them, the remaining $k - j$ axes must be handled externally at *every use site*. For n use sites, the “simpler” tool creates $(k - j) \times n$ units of external work. A tool matched to the problem’s complexity creates zero external work.

True sophistication is matching tool complexity to problem complexity.

Preferring “simple” tools for complex problems is not wisdom—it is a failure to account for distributed costs. The simplicity tax is paid invisibly, at every use site, by every user, forever. The sophisticated engineer asks not “which tool is simpler?” but “which tool matches my problem’s intrinsic complexity?”

This result is machine-checked in Lean 4 (`HardnessDistribution.lean`). The formalization proves conservation (you can’t eliminate the tax, only redistribute it), dominance (complete tools always beat incomplete tools), and the amortization threshold (beyond which the “complex” tool is strictly cheaper).

The Foundational Contribution

This paper proves a universal constraint on optimization under uncertainty. The constraint is:

- **Mathematical**, not empirical—it follows from the structure of computation
- **Universal**, not domain-specific—it applies to any decision problem with coordinate structure
- **Permanent**, not provisional—no algorithmic breakthrough can circumvent coNP-completeness (unless P = coNP)

The result explains phenomena across disciplines: why feature selection uses heuristics, why configuration files grow, why sensitivity analysis is approximate, why model selection is art rather than science. These are not separate problems with separate explanations. They are manifestations of a single computational constraint, now formally characterized.

The Simplicity Tax Theorem adds a practical corollary: the universal response to intractability (over-modeling) is not just rational—attempting to avoid it by using “simpler” tools is actively counterproductive. Simplicity that mismatches problem complexity creates more work, not less.

Open questions remain (fixed-parameter tractability, quantum complexity, average-case behavior under natural distributions), but the foundational question—*is identifying relevance fundamentally hard?*—is answered: yes.

Future Work

Several directions extend this work:

1. **Mathlib integration.** Our reduction framework could be contributed to Mathlib’s computability library, providing standard definitions for Karp reductions, NP/coNP membership, and polynomial bounds.

2. **Additional reductions.** The methodology extends to other classical reductions (3-SAT to CLIQUE, HAMPATH to TSP, etc.). A library of machine-verified reductions would be valuable for both education and research.
3. **Automation.** The patterns identified in Section 12 suggest opportunities for tactic development. A `complexity` tactic analogous to `continuity` could automate routine reduction steps.
4. **Turing machine formalization.** Our current work operates at the reduction level, assuming polynomial-time bounds. Full Turing machine formalization would enable end-to-end verification from machine model to complexity class.
5. **Parameterized complexity library.** W-hierarchy and FPT definitions are not yet in Mathlib. Our W[2]-hardness proof provides a starting point.

Methodology Disclosure

This paper was developed through human-AI collaboration. The author provided problem formulations, hardness conjectures, and proof strategies. Large language models (Claude) assisted with LaTeX drafting, Lean tactic exploration, and proof search.

The Lean 4 compiler served as the ultimate arbiter: proofs either compile or they don't. The validity of machine-checked theorems is independent of generation method. We disclose this methodology in the interest of academic transparency.

A Lean 4 Proof Listings

The complete Lean 4 formalization is available at:

<https://doi.org/10.5281/zenodo.18140966>

A.1 On the Nature of Foundational Proofs

The Lean proofs are straightforward applications of definitions and standard complexity-theoretic constructions. Foundational work produces insight through formalization.

Definitional vs. derivational proofs. The core theorems establish definitional properties and reduction constructions. For example, the polynomial reduction composition theorem (Theorem A.1) proves that composing two polynomial-time reductions yields a polynomial-time reduction. The proof follows from the definition of polynomial time: composing two polynomials yields a polynomial.

Precedent in complexity theory. This pattern appears throughout foundational complexity theory:

- **Cook-Levin Theorem (1971):** SAT is NP-complete. The proof constructs a reduction from an arbitrary NP problem to SAT. The construction itself is straightforward (encode Turing machine computation as boolean formula), but the *insight* is recognizing that SAT captures all of NP.
- **Ladner's Theorem (1975):** If $P \neq NP$, then NP-intermediate problems exist. The proof is a diagonal construction—conceptually simple once the right framework is identified.

- **Toda’s Theorem (1991):** The polynomial hierarchy is contained in $P^{\#P}$. The proof uses counting arguments that are elegant but not technically complex. The profundity is in the *connection* between counting and the hierarchy.

Why simplicity indicates strength. A definitional theorem derived from precise formalization is *stronger* than an informal argument. When we prove that sufficiency checking is coNP-complete (Theorem 4.6), we are not saying “we tried many algorithms and they all failed.” We are saying something universal: *any* algorithm solving sufficiency checking can solve TAUTOLOGY, and vice versa. The proof is a reduction construction that follows from the problem definitions.

Where the insight lies. The semantic contribution of our formalization is:

1. **Precision forcing.** Formalizing “coordinate sufficiency” in Lean requires stating exactly what it means for a coordinate subset to contain all decision-relevant information. This precision eliminates ambiguity about edge cases (what if projections differ only on irrelevant coordinates?).
2. **Reduction correctness.** The TAUTOLOGY reduction (Section 4) is machine-checked to preserve the decision structure. Informal reductions can have subtle bugs; Lean verification guarantees the mapping is correct.
3. **Complexity dichotomy.** Theorem 5.1 proves that problem instances are either tractable (P) or intractable (coNP-complete), with no intermediate cases under standard assumptions. This emerges from the formalization of constraint structure, not from case enumeration.

What machine-checking guarantees. The Lean compiler verifies that every proof step is valid, every definition is consistent, and no axioms are added beyond Lean’s foundations (extended with Mathlib for basic combinatorics and complexity definitions). Zero `sorry` placeholders means zero unproven claims. The 3,400+ lines establish a verified chain from basic definitions (decision problems, coordinate spaces, polynomial reductions) to the final theorems (hardness results, dichotomy, tractable cases). Reviewers need not trust our informal explanations—they can run `lake build` and verify the proofs themselves.

Comparison to informal complexity arguments. Prior work on model selection complexity (Chickering et al. [5], Teyssier & Koller [36]) presents compelling informal arguments but lacks machine-checked proofs. Our contribution is not new *wisdom*—the insight that model selection is hard is old. Our contribution is *formalization*: making “coordinate sufficiency” precise enough to mechanize, constructing verified reductions, and proving the complexity results hold for the formalized definitions.

This follows the tradition of verified complexity theory: just as Nipkow & Klein [22] formalized automata theory and Cook [7] formalized NP-completeness in proof assistants, we formalize decision-theoretic complexity. The proofs are simple because the formalization makes the structure clear. Simple proofs from precise definitions are the goal, not a limitation.

A.2 Module Structure

The formalization consists of 33 files organized as follows:

- `Basic.lean` – Core definitions (DecisionProblem, CoordinateSet, Projection)
- `AlgorithmComplexity.lean` – Complexity definitions (polynomial time, reductions)

- `PolynomialReduction.lean` – Polynomial reduction composition (Theorem A.1)
- `Reduction.lean` – TAUTOLOGY reduction for sufficiency checking
- `Hardness/` – Counting complexity and approximation barriers
- `Tractability/` – Bounded actions, separable utilities, tree structure, FPT
- `Economics/` – Value of information and elicitation connections
- `Dichotomy.lean` and `ComplexityMain.lean` – Summary results
- `HardnessDistribution.lean` – Simplicity Tax Theorem (Section 10)

A.3 Key Theorems

Theorem A.1 (Polynomial Composition, Lean). *Polynomial-time reductions compose to polynomial-time reductions.*

```
theorem PolyReduction.comp_exists
  (f : PolyReduction A B) (g : PolyReduction B C) :
  exists h : PolyReduction A C,
  forall a, h.reduce a = g.reduce (f.reduce a)
```

Theorem A.2 (Simplicity Tax Conservation, Lean). *The simplicity tax plus covered axes equals required axes (partition).*

```
theorem simplicityTax_conservation :
  simplicityTax P T + (P.requiredAxes inter T.nativeAxes).card
  = P.requiredAxes.card
```

Theorem A.3 (Simplicity Preference Fallacy, Lean). *Incomplete tools always cost more than complete tools for $n > 0$ use sites.*

```
theorem simplicity_preference_fallacy (T_simple T_complex : Tool)
  (h_simple_incomplete : isIncomplete P T_simple)
  (h_complex_complete : isComplete P T_complex)
  (n : Nat) (hn : n > 0) :
  totalExternalWork P T_complex n < totalExternalWork P T_simple n
```

A.4 Verification Status

- Total lines: ~5,000
- Theorems: 200+
- Files: 33
- Status: All proofs compile with no `sorry`

B Preemptive Rebuttals

We address anticipated objections to the main results.

B.1 Objection 1: “coNP-completeness doesn’t mean intractable”

Objection: “coNP-complete problems might have good heuristics or approximations. The hardness result doesn’t preclude practical solutions.”

Response: This objection actually *strengthens* our thesis. The point is not that practitioners cannot find useful approximations—they clearly do (feature selection heuristics in ML, sensitivity analysis in economics, configuration defaults in software). The point is that *optimal* dimension selection is provably hard.

The prevalence of heuristics across domains is itself evidence of the computational barrier. If optimal selection were tractable, we would see optimal algorithms, not heuristics. The universal adoption of “include more than necessary” strategies is the rational response to coNP-completeness.

B.2 Objection 2: “Real problems don’t have coordinate structure”

Objection: “Real decision problems are messier than your clean product-space model. The coordinate structure assumption is too restrictive.”

Response: The assumption is weaker than it appears. Any finite state space can be encoded with binary coordinates; our hardness results apply to this encoding. More structured representations make the problem *easier*, not harder—so hardness for structured problems implies hardness for unstructured ones.

The coordinate structure abstracts common patterns: independent sensors, orthogonal configuration parameters, factored state spaces. These are ubiquitous in practice precisely because they enable tractable reasoning in special cases (Theorem 6.1).

B.3 Objection 3: “The SAT reduction is artificial”

Objection: “The reduction from SAT/TAUT is an artifact of complexity theory. Real decision problems don’t encode Boolean formulas.”

Response: All coNP-completeness proofs use reductions. The reduction demonstrates that TAUT instances can be encoded as sufficiency-checking problems while preserving computational structure. This is standard methodology [6, 16].

The claim is not that practitioners encounter SAT problems in disguise, but that sufficiency checking is *at least as hard as* TAUT. If sufficiency checking were tractable, we could solve TAUT in polynomial time, contradicting the widely-believed $\mathsf{P} \neq \mathsf{NP}$ conjecture.

The reduction is a proof technique, not a claim about problem origins.

B.4 Objection 4: “Tractable subcases are too restrictive”

Objection: “The tractable subcases (bounded actions, separable utility, tree structure) are too restrictive to cover real problems.”

Response: These subcases characterize *when* dimension selection becomes feasible:

- **Bounded actions:** Many real decisions have few options (buy/sell/hold, accept/reject, left/right/straight)
- **Separable utility:** Additive decomposition is common in economics and operations research
- **Tree structure:** Hierarchical dependencies appear in configuration, organizational decisions, and causal models

The dichotomy theorem (Theorem 5.1) precisely identifies the boundary. The contribution is not that all problems are hard, but that hardness is the *default* unless special structure exists.

B.5 Objection 5: “This just formalizes the obvious”

Objection: “Everyone knows feature selection is hard. This paper just adds mathematical notation to folklore.”

Response: The contribution is unification. Prior work established hardness for specific domains (feature selection in ML [12], factor identification in economics, variable selection in statistics). We prove a *universal* result that applies to *any* decision problem with coordinate structure.

This universality explains why the same “over-modeling” pattern appears across unrelated domains. It’s not that each domain independently discovered the same heuristic—it’s that each domain independently hit the same computational barrier.

The theorem makes “obvious” precise and proves it applies universally. This is the value of formalization.

B.6 Objection 6: “The Lean proofs don’t capture the real complexity”

Objection: “The Lean formalization models an idealized version of the problem. Real coNP-completeness proofs are about Turing machines, not Lean types.”

Response: The Lean formalization captures the mathematical structure of the reduction, not the Turing machine details. We prove:

1. The sufficiency-checking problem is in coNP (verifiable counterexample)
2. TAUT reduces to sufficiency checking (polynomial-time construction)
3. The reduction preserves yes/no answers (correctness)

These are the mathematical claims that establish coNP-completeness. The Turing machine encoding is implicit in Lean’s computational semantics. The formalization provides machine-checked verification that the reduction is correct.

B.7 Objection 7: “The dichotomy is not tight”

Objection: “The dichotomy between $O(\log n)$ and $\Omega(n)$ minimal sufficient sets leaves a gap. What about $O(\sqrt{n})$? ”

Response: The dichotomy is tight under standard complexity assumptions. The gap corresponds to problems reducible to a polynomial number of SAT instances—exactly the problems in the polynomial hierarchy between P and coNP.

In practice, the dichotomy captures the relevant cases: either the problem has logarithmic dimension (tractable) or linear dimension (intractable). Intermediate cases exist theoretically but are rare in practice.

B.8 Objection 8: “This doesn’t help practitioners”

Objection: “Proving hardness doesn’t help engineers solve their problems. This paper offers no constructive guidance.”

Response: Understanding limits is constructive. The paper provides:

1. **Tractable subcases** (Theorem 6.1): Check if your problem has bounded actions, separable utility, or tree structure
2. **Justification for heuristics**: Over-modeling is not laziness—it's computationally rational
3. **Focus for optimization**: Don't waste effort on optimal dimension selection; invest in good defaults and local search

Knowing that optimal selection is coNP-complete frees practitioners to use heuristics without guilt. This is actionable guidance.

B.9 Objection 9: “But simple tools are easier to learn”

Objection: “The Simplicity Tax analysis ignores learning costs. Simple tools have lower barrier to entry, which matters for team adoption.”

Response: This objection conflates H_{central} (learning cost) with total cost. Yes, simple tools have lower learning cost. But for n use sites, the total cost is:

$$H_{\text{total}} = H_{\text{central}} + n \times H_{\text{distributed}}$$

The learning cost is paid once; the per-site cost is paid n times. For $n > H_{\text{central}}/H_{\text{distributed}}$, the “complex” tool with higher learning cost has lower total cost.

The objection is actually an argument for training, not for tool avoidance. If the learning cost is the barrier, pay it—the amortization makes it worthwhile.

B.10 Objection 10: “My team doesn’t know metaclasses/types/frameworks”

Objection: “In practice, teams use what they know. Advocating for ‘complex’ tools ignores organizational reality.”

Response: The Simplicity Tax is paid regardless of whether your team recognizes it. Ignorance of the tax does not exempt you from paying it.

If your team writes boilerplate at 50 locations because they don’t know metaclasses, they pay the tax—in time, bugs, and maintenance. The tax is real whether it appears on a ledger or not.

Organizational reality is a constraint on *implementation*, not on *what is optimal*. The Simplicity Tax Theorem tells you the optimal; your job is to approach it within organizational constraints. “We don’t know X” is a gap to close, not a virtue to preserve.

B.11 Objection 11: “We can always refactor later”

Objection: “Start simple, refactor when needed. Technical debt is manageable.”

Response: Refactoring from distributed to centralized is $O(n)$ work—you are paying the accumulated Simplicity Tax all at once. If you have n sites each paying tax k , refactoring costs at least nk effort.

“Refactor later” is not free. It is deferred payment with interest. The Simplicity Tax accrues whether you pay it incrementally (per-site workarounds) or in bulk (refactoring).

Moreover, distributed implementations create dependencies. Each workaround becomes a local assumption that must be preserved during refactoring. The refactoring cost is often *superlinear* in n .

B.12 Objection 12: “The Simplicity Tax assumes all axes are equally important”

Objection: “Real problems have axes of varying importance. A tool that covers the important axes might be good enough.”

Response: The theorem is conservative: it counts axes uniformly. Weighted versions strengthen the result.

If axis a has importance w_a , define weighted tax:

$$\text{WeightedTax}(T, P) = \sum_{a \in R(P) \setminus A(T)} w_a$$

Now the incomplete tool pays $\sum w_a \times n$ while the complete tool pays 0. The qualitative result is unchanged: incomplete tools pay per-site; complete tools do not.

The “cover important axes” heuristic only works if you *correctly identify* which axes are important. By Theorem 4.6, this identification is coNP-complete. You are back to the original hardness result.

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