

The Complexity of Decision-Relevant Uncertainty: Why Identifying What Matters Is Harder Than Knowing Everything

Tristan Simas
McGill University
tristan.simas@mail.mcgill.ca

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Abstract

Engineers routinely include irrelevant information in their models. Climate scientists model atmospheric chemistry when predicting regional temperatures. Financial analysts track hundreds of indicators when making portfolio decisions. Software architects specify dozens of configuration parameters when only a handful affect outcomes.

This paper proves that such *over-modeling* is not laziness—it is computationally rational. Identifying precisely which variables are “decision-relevant” is coNP -complete [5, 10], finding the *minimum* set of relevant variables is coNP -complete, and a fixed-coordinate “anchor” version is Σ_2^P -complete [18]. These results formalize a fundamental insight:

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

We introduce the *decision quotient*—a measure of decision-relevant complexity—and prove a complexity dichotomy: checking sufficiency is polynomial when the minimal sufficient set has logarithmic size, but exponential when it has linear size. We identify tractable subcases (bounded actions, separable utilities, tree-structured dependencies) that admit polynomial algorithms.

These are ceiling results: The complexity characterizations are exact (both upper and lower bounds). The theorems quantify universally over all problem instances (\forall), not probabilistically ($\mu = 1$). The dichotomy is complete—no intermediate cases exist under standard assumptions. The tractability conditions are maximal—relaxing any yields hardness. No stronger complexity claims are possible within classical complexity theory.

All results are machine-checked in Lean 4 [7] (3,400+ lines across 25 files, ~ 60 theorems). The Lean formalization proves: (1) polynomial-time reduction composition; (2) correctness of the TAUTOLOGY and $\exists\forall$ -SAT reduction mappings; (3) equivalence of sufficiency checking with coNP/Σ_2^P -complete problems under standard encodings. Complexity classifications (coNP -complete, Σ_2^P -complete) are derived by combining these machine-checked results with the well-known complexity of TAUTOLOGY and $\exists\forall$ -SAT.

Keywords: computational complexity, decision theory, model selection, coNP -completeness, polynomial hierarchy, Lean 4

1 Introduction

This paper establishes a fundamental limit on rational decision-making under uncertainty:

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

This is not metaphor. It is a theorem. Specifically: given a decision problem with n dimensions of uncertainty, *checking* whether a subset of dimensions suffices for optimal action is **coNP**-complete. *Finding* the minimal sufficient subset is **coNP**-complete. These results hold universally—for any decision problem with coordinate structure.

The implications are immediate and far-reaching. Engineers who include “irrelevant” information in their models are not exhibiting poor discipline. They are responding optimally to a computational constraint that admits no workaround. Climate scientists modeling atmospheric chemistry, financial analysts tracking hundreds of indicators, software architects specifying dozens of parameters—all are exhibiting computationally rational behavior. The alternative (identifying precisely which variables matter) requires solving **coNP**-complete problems.

1.1 The Core Problem

Consider a decision problem with actions A and states $S = X_1 \times \cdots \times X_n$ (a product of n coordinate spaces). For each state $s \in S$, some subset $\text{Opt}(s) \subseteq A$ of actions are optimal. The fundamental question is:

Which coordinates are sufficient to determine the optimal action?

A coordinate set $I \subseteq \{1, \dots, n\}$ is *sufficient* if knowing only the coordinates in I determines the optimal action set:

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

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

1.2 Main Results

This paper proves four main theorems:

1. **Theorem 3.6 (Sufficiency Checking is coNP-complete):** Given a decision problem and coordinate set I , determining whether I is sufficient is **coNP**-complete [5, 10].
2. **Theorem 3.7 (Minimum Sufficiency is coNP-complete):** Finding the minimum sufficient coordinate set is **coNP**-complete. (The problem is trivially in Σ_2^P by structure, but collapses to **coNP** because sufficiency equals “superset of relevant coordinates.”)
3. **Theorem 4.1 (Complexity Dichotomy):** Sufficiency checking exhibits a dichotomy:
 - If the minimal sufficient set has size $O(\log |S|)$, checking is polynomial
 - If the minimal sufficient set has size $\Omega(n)$, checking requires exponential time [9].
4. **Theorem 5.1 (Tractable Subcases):** Sufficiency checking is polynomial-time for:
 - Bounded action sets ($|A| \leq k$ for constant k)
 - Separable utility functions ($u(a, s) = f(a) + g(s)$)
 - Tree-structured coordinate dependencies

1.3 The Foundational Principle

The core result transcends the specific application domain:

For any agent facing structured uncertainty, identifying the relevant dimensions of uncertainty is computationally harder than simply observing all dimensions.

This applies to:

- **Machine learning:** Feature selection is intractable in general
- **Economics:** Identifying relevant market factors is intractable
- **Scientific modeling:** Determining which variables matter is intractable
- **Software engineering:** Configuration minimization is intractable

The ubiquity of over-modeling, over-parameterization, and “include everything” strategies across domains is not coincidence. It is the universal rational response to a universal computational constraint.

1.4 Connection to Prior Papers

This paper completes the theoretical foundation established in Papers 1–3:

- **Paper 1 (Typing):** Showed nominal typing dominates structural typing
- **Paper 2 (SSOT):** Showed single source of truth minimizes modification complexity
- **Paper 3 (Leverage):** Unified both as leverage maximization

Paper 4’s contribution: Proves that *identifying* which architectural decisions matter is itself computationally hard. This explains why leverage maximization (Paper 3) uses heuristics rather than optimal algorithms—and why this is not a deficiency but a mathematical necessity.

1.5 Paper Structure

Section 2 establishes formal foundations: decision problems, coordinate spaces, sufficiency. Section 3 proves hardness results with complete reductions. Section 4 develops the complexity dichotomy. Section 5 presents tractable special cases. Section 7 discusses implications for software architecture and modeling. Section 8 surveys related work. Appendix A contains Lean proof listings.

2 Formal Foundations

We formalize decision problems with coordinate structure, sufficiency of coordinate sets, and the decision quotient, drawing on classical decision theory [16, 15].

2.1 Decision Problems with Coordinate Structure

Definition 2.1 (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 2.2 (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 2.3 (Optimizer Map). For state $s \in S$, the *optimal action set* is:

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

2.2 Sufficiency and Relevance

Definition 2.4 (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 2.5 (Minimal Sufficient Set). A sufficient set I is *minimal* if no proper subset $I' \subsetneq I$ is sufficient.

Definition 2.6 (Relevant Coordinate). Coordinate i is *relevant* if it belongs to some minimal sufficient set.

Example 2.7 (Weather Decision). Consider deciding whether to carry an umbrella:

- Actions: $A = \{\text{carry, don't carry}\}$
- Coordinates: $X_1 = \{\text{rain, no rain}\}$, $X_2 = \{\text{hot, cold}\}$, $X_3 = \{\text{Monday, } \dots, \text{Sunday}\}$
- 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.

2.3 The Decision Quotient

Definition 2.8 (Decision Equivalence). For coordinate set I , states s, s' are I -equivalent (written $s \sim_I s'$) if $s_I = s'_I$.

Definition 2.9 (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 2.10 (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). ■

3 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.

3.1 Problem Definitions

Definition 3.1 (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 3.2 (Optimizer Map). For state $s \in S$, define:

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

Definition 3.3 (Sufficient Coordinate Set). A coordinate set $I \subseteq \{1, \dots, n\}$ is *sufficient* if:

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

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

Problem 3.4 (SUFFICIENCY-CHECK). **Input:** Decision problem (A, n, U) and coordinate set $I \subseteq \{1, \dots, n\}$

Question: Is I sufficient?

Problem 3.5 (MINIMUM-SUFFICIENT-SET). **Input:** Decision problem (A, n, U) and integer k

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

3.2 Hardness of SUFFICIENCY-CHECK

Theorem 3.6 (coNP-completeness of SUFFICIENCY-CHECK). *SUFFICIENCY-CHECK is coNP-complete [5, 10].*

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. ■

3.3 Complexity of MINIMUM-SUFFICIENT-SET

Theorem 3.7 (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 3.6. ■

3.4 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 3.8 (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 3.9 (ANCHOR-SUFFICIENCY is Σ_2^P -complete). *ANCHOR-SUFFICIENCY is Σ_2^P -complete [18] (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. ■

3.5 Tractable Subcases

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

Proposition 3.10 (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 3.11 (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.*

3.6 Implications

Corollary 3.12 (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.

3.7 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.

4 Complexity Dichotomy

The hardness results of Section 3 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 4.1 (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): The reduction from TAUTOLOGY in Theorem 3.6 produces instances where the minimal sufficient set has size $\Omega(n)$ (all coordinates are relevant when the formula is not a tautology). Under the Exponential Time Hypothesis (ETH) [9], TAUTOLOGY requires time $2^{\Omega(n)}$, so SUFFICIENCY-CHECK inherits this lower bound. ■

Corollary 4.2 (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)*

This dichotomy explains why some domains admit tractable model selection (few relevant variables) while others require heuristics (many relevant variables).

5 Tractable Special Cases

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

Theorem 5.1 (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*

5.1 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. ■

5.2 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. ■

5.3 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 [14, 11].

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

5.4 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.

6 Why Over-Modeling Is Optimal

The complexity results of Sections 3 and 4 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.

6.1 Configuration Simplification is SUFFICIENCY-CHECK

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

Theorem 6.1 (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 6.2. 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.

6.2 Computational Rationality of Over-Modeling

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

Theorem 6.3 (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 3.6):

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 3.6, 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 6.4 (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 3.7 (assuming $\text{P} \neq \text{coNP}$). ■

Remark 6.5. Corollary 6.4 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.

6.3 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 6.3).

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.

7 Implications for Software Architecture

The complexity results have direct implications for software engineering practice.

7.1 Why Over-Specification Is Rational

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

Corollary 7.1 (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.

7.2 Connection to Leverage Theory

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

Definition 7.2 (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 7.3 (Leverage-ADQ Duality). *High-leverage architectural decisions correspond to low-ADQ configuration subsets: they strongly constrain system behavior with minimal specification.*

7.3 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 2.10), 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.

8 Related Work

8.1 Computational Decision Theory

The complexity of decision-making has been studied extensively. Papadimitriou [13] 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 [2].

8.2 Feature Selection

In machine learning, feature selection asks which input features are relevant for prediction. This is known to be NP-hard in general [3]. Our results show the decision-theoretic analog is coNP-complete for both checking and minimization.

8.3 Value of Information

The value of information (VOI) framework [8] 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.

8.4 Model Selection

Statistical model selection (AIC [1], BIC [17], cross-validation [19]) provides practical heuristics for choosing among models. Our results provide theoretical justification: optimal model selection is intractable, so heuristics are necessary.

9 Conclusion

Methodology and Disclosure

Role of LLMs in this work. This paper was developed through human-AI collaboration. The author provided the core intuitions—the connection between decision-relevance and computational complexity, the conjecture that SUFFICIENCY-CHECK is coNP-complete, and the insight that the

Σ_2^P structure collapses for MINIMUM-SUFFICIENT-SET. Large language models (Claude, GPT-4) served as implementation partners for proof drafting, Lean formalization, and LaTeX generation.

The Lean 4 proofs were iteratively refined: the author specified what should be proved, the LLM proposed proof strategies, and the Lean compiler served as the arbiter of correctness. The complexity-theoretic reductions required careful human oversight to ensure the polynomial bounds were correctly established.

What the author contributed: The problem formulations (SUFFICIENCY-CHECK, MINIMUM-SUFFICIENT-SET, ANCHOR-SUFFICIENCY), the hardness conjectures, the tractability conditions, and the connection to over-modeling in engineering practice.

What LLMs contributed: LaTeX drafting, Lean tactic exploration, reduction construction assistance, and prose refinement.

The proofs are machine-checked; their validity is independent of generation method. We disclose this methodology in the interest of academic transparency.

We have established that identifying decision-relevant information is computationally hard:

- 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 4.1) 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 3.

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 3.6). 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 3.6 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 4.1).** 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 5).** 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 3.7) 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 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 $P = \text{coNP}$)

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.

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.

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 $P \neq \text{NP}$, 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 3.6), 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 3) 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 4.1 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. [4], Teyssier & Koller [20]) 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 [12] formalized automata theory and Cook [6] 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 25 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

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)
```

A.4 Verification Status

- Total lines: 3,400+
- Theorems: ~60
- Files: 25
- Status: All proofs in this directory compile with no `sorry`

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