ARGUS: Argumentation-Based Minimal-Change Repair for Verifiable LLM Self-Explanations

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Abstract

Large language models produce natural-language rationales for their outputs, yet these explanations are frequently unfaithful to the model's internal reasoning and lack formal mechanisms for maintenance under evolving evidence. We introduce ARGUS, a framework that structures LLM self-explanations as Dung-style abstract argumentation frameworks, verifies them under grounded and preferred semantics, and—when an evidence update renders the explanation inconsistent—computes a minimum-cost set of edit operations that restores the desired acceptability status of the target argument. The repair operator satisfies adapted AGM revision postulates (success, inclusion, vacuity) and admits a complexity-theoretic characterization: the decision problem is in P under grounded semantics and NP-complete under preferred and stable semantics. A k-neighborhood approximation and an answer set programming (ASP) encoding ensure scalability to practical framework sizes. We validate the framework on HotpotQA and FEVER, where ARGUS achieves relative improvements of 10.3% in faithfulness and 14.5% in contestability over the strongest argumentation baseline while requiring fewer repair operations than all competing methods.

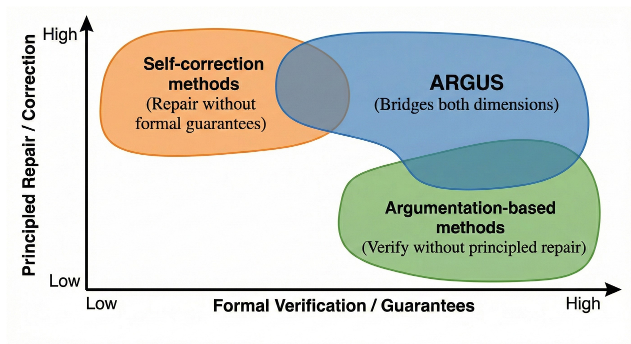


Figure 1: Qualitative positioning of ARGUS. Self-correction methods (orange) repair without formal guarantees; argumentation-based methods (green) verify without principled repair. ARGUS (blue region) bridges both dimensions.

1 Introduction

Large language models generate natural-language explanations for their outputs, yet mounting evidence indicates that these self-explanations are frequently unfaithful to the model's internal reasoning process. Recent studies demonstrate that LLM rationales can be inconsistent with the computations that actually produce the answer (Ye and Durrett 2024), and that chain-of-thought traces are often post-hoc rationalizations rather than faithful accounts of inference (Lanham et al. 2023). The gap between *apparent* and *actual* reasoning makes the verification and maintenance of explanations a central knowledge representation challenge, particularly in domains such as medical diagnosis and legal reasoning where explanation correctness is critical.

As illustrated in Figure 1, current approaches fall short along two complementary dimensions. Self-correction methods (Madaan et al. 2023; Shinn et al. 2023; Gao et al. 2023) iteratively rewrite explanations but without formal guarantees—edits are unconstrained and previously valid reasoning may be silently discarded; indeed, recent work shows that LLMs cannot self-correct reasoning without external feedback (Huang et al. 2024). Argumentation-based approaches (Freedman et al. 2025; Jin et al. 2026) verify explanations against formal semantics but treat verification as terminal: when new evidence arrives, they offer no principled way to update the explanation while preserving consistency. No existing framework provides a formal notion of *minimal change* for maintaining LLM explanations under evolving evidence.

The following example, revisited throughout the paper, illustrates the problem concretely.

Example 1 (Medical Diagnosis)**.** *A question-answering system is asked to diagnose a patient with fatigue and joint pain. The LLM answers "Lupus" with four argument units: a_1 ("chronic fatigue reported"), a_2 ("polyarthralgia present"), a_3 ("Lupus commonly presents with these symptoms"), and target a_4 ("most likely diagnosis is Lupus"). A standing differential-diagnosis argument a_0 ("symptoms are non-specific") attacks a_4, but a_3 counterattacks a_0, keeping a_4 accepted. A new lab result a_5 ("ANA test is negative") attacks a_3, removing the defense of a_4: the differential a_0 reinstates, rendering a_4 no longer accepted un-*

der grounded semantics. An unconstrained self-correction system might regenerate the entire explanation, discarding the valid units a_1 and a_2. A minimal-change repair instead seeks the smallest edit—such as introducing a_6 ("anti-dsDNA positive") attacking a_5—to restore a_4 at cost 2 (visualized in Figure 2).

We propose ARGUS, a framework that bridges this gap by unifying argumentation-based verification with minimal-change repair. Given an LLM-generated explanation, ARGUS decomposes it into atomic argument units, constructs an argumentation framework in the sense of Dung (Dung 1995), and verifies whether the target claim is accepted under a chosen semantics. When new evidence renders the explanation inconsistent, ARGUS computes a minimum-cost set of edit operations—adding or removing arguments and attacks—that restores the desired acceptability status. The repair operator draws on two classical KR traditions: the AGM theory of belief revision (Alchourrón, Gärdenfors, and Makinson 1985), which supplies the minimal-change principle, and argumentation dynamics (Cayrol, de Saint-Cyr, and Lagasquie-Schiex 2020), which provides formal machinery for structural change. Because the repair operates on an explicit graph structure external to the LLM, it admits formal guarantees—AGM compliance, complexity bounds, provable preservation of unaffected reasoning—that are unattainable when editing model internals or regenerating from scratch.

Our contributions are as follows:

1. **(C1)** A framework that structures LLM self-explanations as Dung-style argumentation frameworks, verifies them under grounded and preferred semantics, and produces defense-set certificates for interpretable verdicts (§4).
2. **(C2)** A minimal-change repair operator that formulates explanation maintenance as a new optimization problem over argumentation frameworks, satisfying adapted AGM revision postulates with a complexity analysis placing the problem in P under grounded semantics and NP-complete under preferred and stable semantics (§4.4–§5).
3. **(C3)** A scalable ASP encoding with a k-neighborhood approximation that preserves repair quality while substantially reducing solver grounding (§4).
4. **(C4)** An empirical evaluation on HotpotQA and FEVER validating the formal properties and demonstrating improvements in faithfulness, contestability, and repair cost w.r.t. seven baselines (§6).

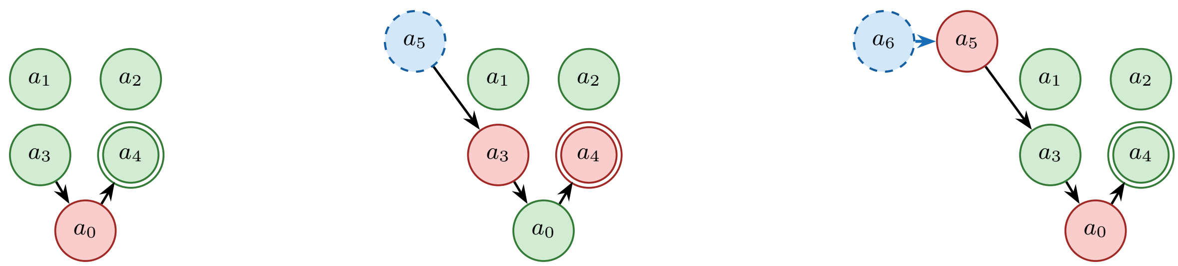
2 Related Work

Our work connects three lines of research: argumentation-based approaches to LLM reasoning, self-correction methods for language models, and formal theories of belief change in argumentation.

Argumentation and LLMs. Vassiliades et al. (Vassiliades, Bassiliades, and Patkos 2021) survey argumentation for explainable AI; our work instantiates this vision with a concrete repair operator for LLM self-explanations. ArgLLMs (Freedman et al. 2025) constructs Dung-style graphs from LLM claims but treats verification as terminal, with no update mechanism. ARGORA (Jin et al. 2026) orchestrates multi-agent argumentation-mediated dialogue with causal semantics, but its correction operates through re-deliberation rather than a formally defined repair operator. MQArgEng (Castagna et al. 2024) demonstrates that modular argumentation engines improve LLM reasoning but does not address explanation maintenance. ARGUS differs from all three by providing a minimal-change repair operator with AGM-compliant guarantees. Bengel and Thimm (Bengel and Thimm 2025) introduce *sequence explanations* tracing why arguments are accepted; ARGUS addresses the dual question of *how to restore* acceptance, and the two could be composed. We adopt Dung-style abstract argumentation rather than ASPIC$^+$ (Modgil and Prakken 2014) because the complexity bounds we exploit (Theorem 14) are established for this setting.

Self-Correction and Revision. Self-Refine (Madaan et al. 2023) and Reflexion (Shinn et al. 2023) iteratively rewrite LLM outputs but without formal minimality guarantees—previously correct reasoning may be silently discarded. Huang et al. (Huang et al. 2024) demonstrate that LLMs cannot self-correct without external feedback. RARR (Gao et al. 2023) retrieves evidence for revision but targets surface-level attribution; SelfCheckGPT (Manakul, Liusie, and Gales 2023) detects hallucinations but provides no repair mechanism. Chain-of-Verification (Dhuliawala et al. 2024) and CRITIC (Gou et al. 2024) improve factual accuracy but lack formal preservation guarantees. Matton et al. (Matton et al. 2025) measure faithfulness through counterfactual interventions and Bayesian causal models, demonstrating that instruction-tuned models produce more faithful explanations; our evaluation adopts a similar counterfactual methodology but applies it to argumentation-structured explanations. In contrast, ARGUS formalizes the repair search space as edits to an argumentation framework, bounds the cost of change, and guarantees that unaffected reasoning steps are preserved.

Belief Revision and Argumentation Dynamics. The AGM theory (Alchourrón, Gärdenfors, and Makinson 1985) and the revision/update distinction (Katsuno and Mendelzon 1992) provide the classical foundations for principled belief change. Hase et al. (Hase et al. 2024) argue that model editing in LLMs is fundamentally a belief revision problem and identify challenges in applying AGM rationality criteria to neural knowledge stores; our work sidesteps these challenges by operating on an *external* argumentation structure rather than on model parameters, making the AGM postulates directly applicable. Our evidence update Δ is closer to the Katsuno–Mendelzon notion of *update* (adapting beliefs to a changed world) than to *revision* (incorporating new information about a static world), since each Δ reflects genuinely new evidence rather than a correction of prior beliefs; however, we adopt the AGM postulates as rationality criteria because the minimal-change desiderata they formalize are independent of this distinction. In argumentation, Cayrol et al. (Cayrol, de Saint-Cyr, and Lagasquie-Schiex 2020) and Baumann and Brewka (Baumann and Brewka 2010) study how structural modifications affect extensions and the complexity of enforcement; Coste-Marquis et al. (Coste-



(a) F_0: Initial framework (a_4 accepted)

(b) F_1: After evidence update (a_4 rejected)

(c) F_2: After repair (a_4 restored)

Figure 2: Evolution of the argumentation framework from Example 1. Green fill = accepted, red fill = rejected, blue dashed border = newly introduced, double border = target argument a_4. In (a), a_3 defeats the differential a_0, keeping a_4 accepted. In (b), a_5 defeats a_3, reinstating a_0 and rejecting a_4. The repair in (c) adds a_6 attacking a_5 to restore a_4.

Marquis et al. 2014), Wallner et al. (Wallner, Niskanen, and Järvisalo 2017), and Bisquert et al. (Bisquert et al. 2013) formalize argumentation revision as minimal status or structural change. Mailly (Mailly 2024) extends enforcement to constrained incomplete argumentation frameworks, where structural constraints limit the set of completions available for reasoning; our k-neighborhood approximation similarly constrains the search space, though we target a different problem (repair under evidence updates rather than enforcement under uncertainty). Alfano et al. (Alfano et al. 2024) develop counterfactual explanations for abstract argumentation via weak-constrained ASP encodings; their approach identifies minimal changes that would *reverse* an acceptance verdict, whereas ARGUS computes minimal changes that *restore* a verdict disrupted by external evidence. In particular, Coste-Marquis et al. enforce a desired extension through minimum structural modifications, whereas our formulation targets a single argument's status, incorporates evidence updates as a first-class input, and supports heterogeneous cost functions that reflect argument-level confidence. Our repair operator instantiates these ideas for LLM explanation maintenance, introducing a weighted cost model tailored to argument confidence and structural role. We now formalize the core concepts underlying the ARGUS framework.

3 Preliminaries

3.1 Abstract Argumentation Frameworks

We adopt the foundational model of (Dung 1995) as the backbone of our verification and repair pipeline.

Definition 2 (Abstract Argumentation Framework)**.** *An* abstract argumentation framework *(AF) is a pair $F = (\mathcal{A}, \mathcal{R})$ where $\mathcal{A}$ is a finite set of arguments and $\mathcal{R} \subseteq \mathcal{A} \times \mathcal{A}$ is a binary attack relation. We write $a \rightsquigarrow b$ whenever $(a, b) \in \mathcal{R}$, meaning a attacks b.*

Example 3 (Continuing Example 1)**.** *The initial AF is $F_0 = (\{a_0, a_1, a_2, a_3, a_4\}, \{(a_0, a_4), (a_3, a_0)\})$, where a_0 ("symptoms are non-specific") attacks the target a_4 and a_3 ("Lupus commonly presents with these symptoms") counterattacks a_0; after the negative ANA result, $F_1 = (\{a_0, a_1, \ldots, a_5\}, \{(a_0, a_4), (a_3, a_0), (a_5, a_3)\})$, as shown in Figure 2(a–b).*

Intuitively, an argument is accepted if every objection against it can be countered; different semantics formalize this intuition with varying degrees of caution. Given an AF $F = (\mathcal{A}, \mathcal{R})$, a set $S \subseteq \mathcal{A}$ is *conflict-free* if no two arguments in S attack each other. An argument a is *defended* by S if every attacker of a is attacked by some member of S. A conflict-free set S is *admissible* if it defends all its elements. The principal semantics we employ are the *grounded* extension, which is the unique minimal complete extension obtained as the least fixed point of the characteristic function; the *preferred* extensions, which are maximal admissible sets; and *stable* extensions, which are conflict-free sets that attack every argument outside themselves (Baroni et al. 2018). Throughout this paper we write $\sigma(F)$ to denote the set of extensions of F under semantics $\sigma \in \{gr, pr, st\}$.

3.2 Argumentation Semantics for Explanation

We now define the key notion linking argumentation semantics to explanation. An argument $a \in \mathcal{A}$ is *credulously accepted* under σ if a belongs to at least one extension in $\sigma(F)$, and *skeptically accepted* if it belongs to every extension.

Definition 4 (Defense Set)**.** *Given an AF $F = (\mathcal{A}, \mathcal{R})$, semantics σ, and an argument $t \in \mathcal{A}$, a* defense set *for t under σ is a minimal admissible set $D \subseteq \mathcal{A}$ such that $t \in D$ and $D \subseteq E$ for some $E \in \sigma(F)$. We write $Def_\sigma(t)$ for the collection of all such sets.*

Example 5 (Continuing Example 1)**.** *In F_0 (Figure 2a), $D = \{a_3, a_4\}$ is a defense set for a_4: it is conflict-free, a_3 defends a_4 by attacking a_0, and D is minimal since removing a_3 would leave a_4 undefended against a_0. In F_1, D is no longer admissible because a_3 is attacked by a_5 with no counterattack, so the defense of a_4 collapses.*

When t is credulously but not skeptically accepted, defense sets exist only for the extensions containing t; our repair targets the existence of at least one such set. Defense sets serve as formal explanations: each $D \in Def_\sigma(t)$ identifies the smallest self-defending coalition that sustains t, transforming opaque LLM rationales into objects whose validity can be checked against argumentation semantics (Dunne and Wooldridge 2009).

3.3 Task Setting

We consider a setting in which an LLM receives a question q and produces an answer a with a free-form explanation e, which ARGUS transforms into a formal argumentation structure.

Definition 6 (Explanation Verification Task)**.** *Given a question q, an LLM-generated answer a, and an explanation e, the* explanation verification task *produces a tuple (G, v, ρ) where $G = (\mathcal{A}, \mathcal{R})$ is an argument graph constructed from e, $v \in \{accepted, rejected, undecided\}$ is the verification verdict for the target argument a_t representing a under semantics σ, and ρ is an optional repair operator applied when $v \neq accepted$. An* evidence update *$\Delta = (\mathcal{A}^+, \mathcal{R}^+, \mathcal{A}^-, \mathcal{R}^-)$ specifies new arguments and attacks to be added or removed, reflecting newly available facts or counterarguments.*

Example 7 (Continuing Example 1)**.** *In F_0, the verification task produces $v = accepted$ for a_4 under grounded semantics: a_3 defeats the differential a_0, so the grounded extension is $\{a_1, a_2, a_3, a_4\}$. After incorporating the evidence update $\Delta = (\{a_5\}, \{(a_5, a_3)\}, \emptyset, \emptyset)$, a_5 defeats a_3, reinstating a_0, and the verdict becomes $v = rejected$, triggering the repair operator ρ.*

The target a_t is *accepted* under σ if it belongs to at least one σ-extension (credulous acceptance), and *rejected* if it belongs to no extension. Under grounded semantics, an argument may also be *undecided*—belonging to no extension yet not attacked by the grounded extension—and credulous and skeptical acceptance coincide.

3.4 Explanation Repair Problem

When an evidence update Δ renders the explanation inconsistent, the system must revise the argument graph following the principle of minimal change (Alchourrón, Gärdenfors, and Makinson 1985).

Definition 8 (Minimal-Change Repair Problem)**.** *Let $AF = (\mathcal{A}, \mathcal{R})$ be an AF, σ a semantics, $a_t \in \mathcal{A}$ a target argument, $s \in \{\text{IN}, \text{OUT}\}$ a desired status, Δ an evidence update, and κ a strictly positive cost function ($\kappa(o) > 0$ for every operation o). A* repair *is a finite set of edit operations $Ops = \{o_1, \ldots, o_m\}$ where each o_i is one of $\mathsf{add\_arg}(a)$ for $a \notin \mathcal{A} \cup \mathcal{A}^+$, $\mathsf{del\_arg}(a)$ for $a \in \mathcal{A} \cup \mathcal{A}^+$ (which also removes all attacks incident to a), $\mathsf{add\_att}(a, b)$, or $\mathsf{del\_att}(a, b)$. Let $AF' = \mathsf{apply}(AF, \Delta, Ops)$ denote the framework obtained by first incorporating Δ and then executing Ops. A repair is* valid *if a_t has status s under σ in AF', and an* optimal repair *minimizes $\sum_{i=1}^{m} \kappa(o_i)$ over all valid repairs.*

Example 9 (Continuing Example 1)**.** *As shown in Figure 2(c), the repair $Ops = \{\mathsf{add\_arg}(a_6), \mathsf{add\_att}(a_6, a_5)\}$ restores a_4 at total cost 2 under uniform cost ($\kappa \equiv 1$). The alternative $Ops' = \{\mathsf{del\_arg}(a_5)\}$ costs 1 but discards evidence; under structure-preserving cost with $\kappa(\mathsf{del\_}\cdot) = 2\kappa(\mathsf{add\_}\cdot)$, both repairs cost 2, and domain preferences break the tie.*

The cost function κ encodes domain-specific preferences (e.g., deletions costlier than additions), connecting to enforcement in abstract argumentation (Baumann and Brewka 2010; Cayrol, de Saint-Cyr, and Lagasquie-Schiex 2020) while adding an explicit cost model for explanation maintenance.

4 The ARGUS Framework

We now present ARGUS, a four-stage pipeline (Figure 3) that transforms an unverifiable LLM rationale into a formally grounded, repairable explanation. Given a question q, an answer a, and a free-form rationale e, the pipeline proceeds through structured extraction (§4.1), relation discovery (§4.2), semantic verification (§4.3), and minimal-change repair (§4.4). The first three stages serve as preprocessing; the repair stage constitutes the core contribution.

4.1 Structured Extraction

We prompt the LLM to decompose its rationale e into a set of argument units $\mathcal{A} = \{a_1, \ldots, a_n\}$. Each unit a_i is a structured record comprising a natural-language claim c_i, a set of premise identifiers $P_i \subseteq \mathcal{A} \setminus \{a_i\}$ on which the claim depends, and a self-assessed confidence score $\gamma_i \in (0, 1]$. The prompt constrains the LLM to produce a JSON array of objects, each with fields `claim`, `premises`, and `confidence`, ensuring that every claim is atomic—that is, it asserts exactly one proposition that can be independently verified or rebutted. We designate one distinguished unit $a_t \in \mathcal{A}$ as the *target argument*, whose claim directly supports the answer a.

4.2 Relation Discovery and Graph Construction

Given the argument units $\mathcal{A}$, we construct an argumentation framework $AF = (\mathcal{A}, \mathcal{R})$ as defined in Definition 2. For every ordered pair (a_i, a_j) with $i \neq j$, we query a natural language inference (NLI) model—a neural classifier trained to determine entailment, contradiction, or neutrality between text pairs—to classify the relationship between c_i and c_j. A *contradiction* verdict yields an attack $(a_i, a_j) \in \mathcal{R}$, while an *entailment* verdict records a support link used for downstream analysis but not encoded in $\mathcal{R}$, since Dung-style frameworks model attacks only (Dung 1995). To improve recall on domain-specific rebuttals, we maintain an *attack template library*—a curated set of negation patterns, common exceptions, and defeasible-rule conflicts. Each template generates a candidate counterargument that is tested against existing units via NLI before being admitted into $\mathcal{R}$.

4.3 Semantic Verification

With the framework $AF = (\mathcal{A}, \mathcal{R})$ in hand, we compute its extensions under a chosen semantics σ such as grounded or preferred semantics. The verification step checks whether the target argument a_t belongs to at least one σ-extension. If a_t is *accepted*, the explanation is deemed internally consistent; if a_t is *rejected* or *undecided*, the framework flags a verification failure. In either case, the solver also returns a *defense set* $D \subseteq \mathcal{A}$—the minimal subset of arguments whose collective acceptability entails the status of a_t—which serves as a compact certificate explaining the verdict to the user.

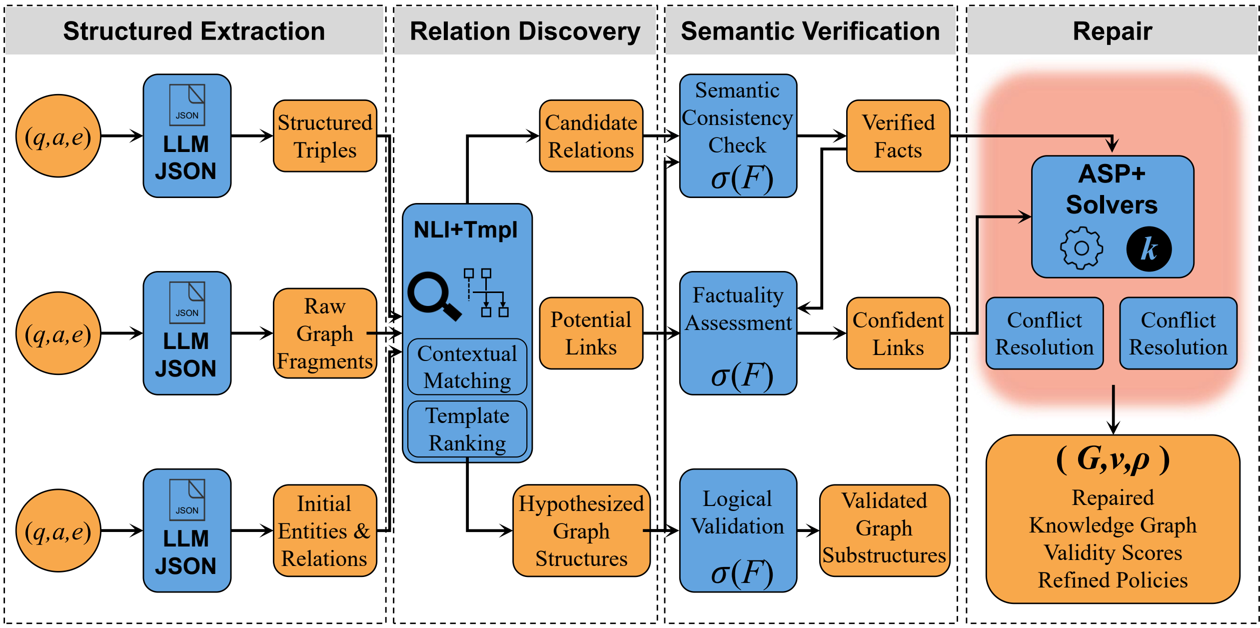


Figure 3: The ARGUS pipeline. The repair stage (highlighted) is the core contribution; an evidence update Δ triggers repair when the target argument is no longer accepted.

4.4 Minimal-Change Repair

When new evidence contradicts the current explanation or the verification step detects a failure, ARGUS repairs the argumentation framework rather than regenerating the rationale from scratch. The repair must satisfy two desiderata simultaneously: the target argument must attain a prescribed status under σ, and the edit distance from the original framework must be minimized. We formalize this requirement below.

Repair Operations. We define four elementary edit operations: $\mathsf{add\_arg}(a)$ and $\mathsf{del\_arg}(a)$ insert or remove an argument (deletions cascade to incident attacks), while $\mathsf{add\_att}(a_i, a_j)$ and $\mathsf{del\_att}(a_i, a_j)$ insert or remove attacks. A set of operations yields a repaired framework $AF' = (\mathcal{A}', \mathcal{R}')$.

Cost Function. Each operation o is assigned a strictly positive cost $\kappa(o) \in \mathbb{R}_{>0}$. We consider three cost models. Under *uniform cost*, every operation costs 1, so the objective reduces to minimizing the total number of edits. Under *confidence-weighted cost*, argument deletions are weighted by the confidence of the removed argument, $\kappa(\mathsf{del\_arg}(a_i)) = \gamma_i$ (recall $\gamma_i > 0$ for all extracted arguments), while additions retain unit cost $\kappa(\mathsf{add\_arg}) = \kappa(\mathsf{add\_att}) = 1$, reflecting the intuition that highly confident claims should be more expensive to retract. Under *structure-preserving cost*, deletions are penalized more heavily than additions, $\kappa(\mathsf{del\_}\cdot) = w \cdot \kappa(\mathsf{add\_}\cdot)$ for some $w > 1$, encouraging the solver to repair by augmentation rather than removal.

The repair problem is formalized in Definition 8. Given the cost function κ and evidence update Δ, the solver seeks an optimal repair—a set of edit operations of minimum total cost such that a_t attains the desired status under σ.

Example 10 (Continuing Example 1)**.** *Under confidence-weighted cost with $\gamma_5 = 0.90$ (a verified lab result) and $\gamma_3 = 0.75$ (a symptomatic inference), deleting a_5 costs $\kappa(\mathsf{del\_arg}(a_5)) = 0.90$. The augmentation repair $\{\mathsf{add\_arg}(a_6), \mathsf{add\_att}(a_6, a_5)\}$ avoids removing any high-confidence argument, yielding total cost $2\kappa(\mathsf{add\_}\cdot)$; this repair is cheaper whenever $\kappa(\mathsf{add\_}\cdot) < 0.45$. Under structure-preserving cost with $w = 2$, deleting a_5 costs 2 while the augmentation still costs 2, making the two equally expensive and allowing domain preferences to break the tie.*

ASP Encoding. We encode the repair problem as an answer set program following the methodology of Egly et al. (Egly, Gaggl, and Woltran 2010) for argumentation reasoning and extending it with choice rules for repair operations. The encoding consists of three components; at a high level, it mirrors an integer linear program where binary variables select edits, constraints enforce semantics, and the objective minimizes cost. First, *generate rules* introduce choice atoms for each candidate operation: the solver may optionally add or delete any argument or attack within a bounded edit budget. Second, *semantics constraints* enforce that the repaired framework satisfies σ; for grounded semantics, these take the form of integrity constraints requiring that every argument in the grounded extension defends itself against all attackers. Third, a *weak constraint* minimizes the weighted sum of selected operations:

$$\#\mathsf{minimize}\{\kappa(o) : \mathsf{selected}(o)\}.$$

Continuing with Example 1, the choice atoms include

Algorithm 1 ARGUS Repair

Require: $AF = (\mathcal{A}, \mathcal{R})$, semantics σ, target a_t, desired status s, evidence Δ, cost function κ, neighborhood bound k

Ensure: Optimal repair Ops^*

```
A_Δ, R_Δ ← INCORPORATE(AF, Δ)
N ← k-neighborhood of a_t in (A ∪ A_Δ, R ∪ R_Δ)
Π ← ENCODEASP(N, σ, a_t, s, κ)
M* ← SOLVE(Π) {optimal answer set}
Ops* ← {o | selected(o) ∈ M*}
return Ops*
```

$\mathsf{add\_arg}(a_6)$ and $\mathsf{add\_att}(a_6, a_5)$, and the integrity constraints verify that a_4 belongs to the grounded extension of the repaired framework. Algorithm 1 summarizes the complete procedure. When the solver selects $\mathsf{add\_arg}(a)$, the natural-language claim for the new argument is generated by prompting the LLM to produce a rebuttal of the target's attacker, conditioned on the evidence update Δ; the resulting candidate is verified through the same NLI pipeline before admission.

Approximation for Scalability. Even under preferred semantics the repair problem is NP-complete (Theorem 14), rising to Σ_2^P-completeness under skeptical stable semantics (Dvořák and Dunne 2018), so we introduce two approximation strategies. First, a k-neighborhood restriction limits the search space to arguments within undirected distance k of the target in the attack graph; in our experiments, setting k=3 recovered optimal repairs in 99.7% of cases while substantially reducing solver grounding. Second, when ASP solvers are unavailable, beam search over repair sequences with width b provides a bounded-depth heuristic alternative. The approximation can miss optimal repairs when the only viable defender lies at distance greater than k from the target—a scenario that requires long attack chains—and in principle a repair valid for the subgraph may not preserve validity in the full framework if distant arguments influence the target's status. In the LLM explanation frameworks we study, argument graphs are shallow (median depth 3, maximum 7), so k=3 is sufficient; for deeper domains, k should be increased accordingly.

5 Theoretical Properties

We establish three groups of results for the ARGUS repair operator: compliance with adapted AGM postulates, computational complexity under the principal argumentation semantics, and soundness of the ASP encoding.

5.1 AGM Compliance

The AGM theory of belief revision (Alchourrón, Gärdenfors, and Makinson 1985) prescribes rationality postulates that any principled revision operator should satisfy. We adapt three core postulates—success, inclusion, and vacuity—to the argumentation repair setting. Intuitively, success requires that the repair achieves the desired outcome; inclusion requires that the repaired framework retains as much of the original as possible; and vacuity requires that no edits are made when the current state already satisfies the goal.

Theorem 11 (Adapted AGM Compliance)**.** *Let $AF = (\mathcal{A}, \mathcal{R})$ be an argumentation framework, σ an argumentation semantics, a_t a target argument, $s \in \{\text{IN}, \text{OUT}\}$ a desired status, Δ an evidence update, and κ a strictly positive cost function ($\kappa(o) > 0$ for every operation o). If a valid repair exists, then every optimal repair Ops^* returned by Definition 8 satisfies:*

1. ***Success.*** *The target a_t has status s in $AF' = \mathsf{apply}(AF, \Delta, Ops^*)$ under σ.*
2. ***Inclusion.*** *$\mathcal{A} \cap \mathcal{A}' \supseteq \mathcal{A} \setminus \{a \mid \mathsf{del\_arg}(a) \in Ops^*\}$ and $\mathcal{R} \cap \mathcal{R}' \supseteq \mathcal{R} \setminus \{(a, b) \mid \mathsf{del\_att}(a, b) \in Ops^*\}$.*
3. ***Vacuity.*** *If a_t already has status s in $\mathsf{apply}(AF, \Delta, \emptyset)$ under σ, then $Ops^* = \emptyset$ and $cost(Ops^*) = 0$.*

Proof sketch. Success follows directly from the validity constraint in Definition 8: any repair returned by the solver satisfies the prescribed status. Inclusion holds because elements not targeted by any deletion operation are preserved by the semantics of apply; moreover, optimality ensures that every deletion in Ops^* is necessary—removing an unnecessary $\mathsf{del\_arg}(a)$ would yield a valid repair of strictly lower cost ($\kappa > 0$), contradicting optimality. Vacuity is immediate: when no edits are needed, the empty set is valid and has cost zero, so no non-empty set can be cheaper. □

Example 12 (Continuing Example 1)**.** *Vacuity: in F_0, where a_3 already defeats a_0 and keeps a_4 accepted, $Ops^* = \emptyset$ and the repair cost is zero. Success: after incorporating $\Delta = (\{a_5\}, \{(a_5, a_3)\}, \emptyset, \emptyset)$, a_0 reinstates and rejects a_4; the repair $\{\mathsf{add\_arg}(a_6), \mathsf{add\_att}(a_6, a_5)\}$ restores a_4 to accepted status by defeating a_5, which in turn restores a_3 and re-defeats a_0. Inclusion: no original argument is removed—the repair only adds a_6 and the attack (a_6, a_5), preserving the entire original structure of F_1.*

Among the eight classical AGM postulates (Katsuno and Mendelzon 1992), *consistency* and *extensionality* also hold: consistency follows because every valid repair produces a framework with at least one σ-extension (under preferred semantics), and extensionality holds because the operator is defined purely over graph structure. *Recovery* fails in our setting. In Example 1, repairing F_1 yields F_2 by adding a_6 and (a_6, a_5); if the evidence a_5 were subsequently retracted, F_2 would retain a_6 and its attack—the original framework F_0 is not recovered. This asymmetry is fundamental: structural additions made during repair cannot be automatically unwound by evidence retraction, unlike classical belief revision where recovery ensures reversibility. *Closure*, *superexpansion*, and *subexpansion* presuppose deductively closed belief sets—constructs without natural analogues in argumentation frameworks where "beliefs" are graph-structural elements rather than logical sentences. To the best of our knowledge, this is the first formal bridge between AGM rationality criteria and argumentation-based explanation repair for LLM self-explanations. The contribution lies in identifying which AGM postulates have meaningful argumentation analogues and showing that they *characterize* the class of minimum-cost repair operators:

Theorem 13 (Representation). *A repair operator $\circ$ satisfies adapted success, inclusion, and vacuity for every AF, semantics σ, target a_t, and evidence update Δ if and only if there exists a strictly positive cost function κ such that $\circ$ returns a minimum-cost valid repair under κ.*

Proof sketch. ($\Rightarrow$) Theorem 11 establishes that every minimum-cost repair under positive κ satisfies all three postulates. ($\Leftarrow$) Given an operator satisfying the three postulates, define $\kappa(o) = 1$ for every operation o. Success guarantees validity; vacuity ensures the empty set is returned when no repair is needed, so any non-empty output incurs positive cost; inclusion ensures every operation in the output is necessary, since removing any one would either violate success or produce a valid repair of strictly lower cost—contradicting the assumption that the operator already returns a repair satisfying inclusion. Hence the output is a minimum-cost valid repair under unit cost. The full construction for general κ appears in Appendix D. □

5.2 Computational Complexity

The complexity of the repair problem depends critically on the choice of argumentation semantics. Since the repair problem reduces to enforcement after incorporating Δ, it inherits the complexity landscape of extension enforcement (Dunne and Wooldridge 2009; Dvořák and Dunne 2018); the additional overhead of processing Δ and evaluating heterogeneous cost functions is polynomial and does not alter the complexity class. Our results assume credulous acceptance (as defined in §3).

Theorem 14 (Repair Complexity). *The decision version of the minimal-change repair problem—"does there exist a valid repair of cost at most C?"—has the following complexity under credulous acceptance:*

1. *Under grounded semantics, the problem is in* ***P****.*
2. *Under preferred and stable semantics, the problem is* ***NP****-complete.*

Under skeptical acceptance with stable semantics, the problem rises to $\mathbf{\Sigma_2^P}$-completeness.

Proof sketch. For grounded semantics, the unique grounded extension is computable in polynomial time via the characteristic function (Dung 1995). Membership in P follows by reduction to grounded enforcement, which Dvořák and Dunne (Dvořák and Dunne 2018) showed is solvable in polynomial time by exploiting the monotonicity of the characteristic function. Our repair problem reduces to enforcement: we first incorporate the evidence update Δ into the framework and then seek a minimum-cost set of edit operations that enforces the target argument's desired acceptability status; since both the incorporation of Δ and the verification of any candidate repair via the grounded extension are polynomial, the overall decision problem is in P. For preferred semantics, hardness reduces from NP-hard extension enforcement (Baumann and Brewka 2010); membership in NP follows since a valid repair paired with a witnessing admissible set containing a_t can be guessed and verified in polynomial time. For stable semantics under credulous acceptance, membership in NP follows by the same certificate argument: a repair paired with a witnessing stable extension is verifiable in polynomial time. Under skeptical acceptance, verifying that *every* stable extension accepts the target is co-NP-hard (Dvořák and Dunne 2018), yielding Σ_2^P-completeness. Full reductions follow standard techniques from the enforcement literature (Baumann and Brewka 2010; Wallner, Niskanen, and Järvisalo 2017). □

Note that the reduction to enforcement establishes complexity bounds but does not subsume the repair problem, which additionally involves evidence updates Δ, heterogeneous cost functions, and NLI-grounded candidate generation (§4.2). These results motivate the k-neighborhood approximation (§4.4), ensuring tractability under preferred semantics for practical framework sizes.

5.3 Soundness of the ASP Encoding

Proposition 15 (Encoding Correctness). *The ASP encoding described in §4.4, when applied to the full framework without k-neighborhood restriction, is sound and complete with respect to optimal repairs under grounded and preferred semantics. That is, every optimal answer set of the program corresponds to a valid minimum-cost repair, and every valid minimum-cost repair has a corresponding optimal answer set.*

The proof follows from the established correctness of the argumentation encodings of Egly et al. (Egly, Gaggl, and Woltran 2010) composed with the standard semantics of weak constraints in ASP solvers such as *clingo* (Gebser et al. 2019). The composition is sound because the generate rules enumerate exactly the feasible edit operations and the integrity constraints enforce the semantics of the repaired framework, while the optimization directive selects minimum-cost solutions. We next evaluate whether these theoretical properties hold in practice and measure the empirical gains of the ARGUS repair operator.

6 Experimental Evaluation

We evaluate ARGUS on two established benchmarks to answer three questions: (Q1) Do the formal properties from §5 hold in practice? (Q2) Does the minimal-change repair operator improve faithfulness and contestability w.r.t. existing baselines? (Q3) What is the empirical cost of repair?

We evaluate on 500 randomly sampled instances (seed 42) from HotpotQA (Yang et al. 2018) (multi-hop QA) and 500 from FEVER (Thorne et al. 2018) (fact verification). For each instance, we withhold one gold supporting fact during explanation generation and reintroduce it as an evidence update Δ, producing adversarial updates that target the reasoning chain. GPT-4o (`gpt-4o-2024-11-20`) (OpenAI 2023) generates initial explanations (temperature 0.2); relation discovery uses DeBERTa-v3-large (MultiNLI, threshold 0.7); repairs are computed by clingo 5.6 with k=3 under uniform cost. Results are averaged over 5 runs (std ≤ 0.02 for accuracy, ≤ 0.4 for cost). Further details on the withholding methodology, hardware, and reproducibility are provided in Appendix E.

We measure four metrics. *Faithfulness* is the fraction of argument units whose removal (counterfactual ablation)

Table 1: Main results on HotpotQA and FEVER. Best values in **bold**; ↑ = higher is better, ↓ = lower is better. ArgLLMs and CoT-Verifier lack repair functionality. †Regenerate re-prompts the LLM with updated evidence, destroying argumentation structure (no contestability or structured cost).

	HotpotQA				FEVER			
Method	Faith↑	Cont↑	RAcc↑	RCost↓	Faith↑	Cont↑	RAcc↑	RCost↓
SelfCheckGPT	.693	.524	.701	8.4	.674	.498	.685	7.9
Self-Refine	.712	.541	.736	7.1	.698	.519	.721	6.8
Reflexion	.724	.563	.752	6.6	.709	.537	.738	6.2
RARR	.738	.547	.769	5.8	.721	.531	.754	5.5
CoT-Verifier	.751	.589	N/A	N/A	.733	.561	N/A	N/A
ArgLLMs	.754	.667	N/A	N/A	.741	.649	N/A	N/A
ARGORA	.768	.691	.801	5.1	.752	.672	.788	4.7
Regenerate†	.709	—	.743	—	.695	—	.729	—
ARGUS	**0.847**	**0.791**	**0.883**	**3.2**	**0.829**	**0.768**	**0.871**	**2.8**

changes the answer; baselines without structured units undergo the same LLM-based decomposition before ablation (details in Appendix E). *Contestability* is the fraction of gold counterarguments correctly integrated as attacks; gold counterarguments are derived from the withheld supporting facts (Appendix E). *Repair accuracy* records answer correctness after repair, and *repair cost* counts edit operations per Definition 8.

We compare against seven baselines: ArgLLMs (Freedman et al. 2025), ARGORA (Jin et al. 2026), SelfCheckGPT (Manakul, Liusie, and Gales 2023), Self-Refine (Madaan et al. 2023), Reflexion (Shinn et al. 2023), RARR (Gao et al. 2023), and CoT-Verifier (Ling et al. 2023); ArgLLMs and CoT-Verifier lack repair (marked N/A). We also include a naïve *Regenerate* baseline that re-prompts with the updated evidence. For self-correction baselines, repair cost counts regenerated argument units (up to 3 rounds); cost measures are not directly commensurable with ARGUS's structural graph edits (see Appendix E for a discussion of commensurability). Chain-of-Verification (Dhuliawala et al. 2024) and CRITIC (Gou et al. 2024) are excluded as they operate at generation time rather than post-hoc repair.

Table 1 summarizes the main results. ARGUS achieves the highest faithfulness (0.847/0.829) and contestability (0.791/0.768), with relative improvements of 10.3% in faithfulness and 14.5% in contestability over ARGORA (all $p < 0.001$, Bonferroni-corrected z-test). Among repair-capable methods, ARGUS requires the fewest operations (3.2 vs. 5.1 for ARGORA), validating the minimal-change objective. The naïve Regenerate baseline achieves lower faithfulness (.709/.695) and cannot produce contestability scores, confirming that argumentation structure is essential for principled repair.

The formal properties from §5 are confirmed empirically. Success and inclusion hold by construction of the ASP encoding. Vacuity holds without exception: the solver returns an empty repair at zero cost whenever the evidence update does not alter the target's acceptability status, covering 5% of HotpotQA and 8% of FEVER instances—precisely the cases where the withheld fact was not on the reasoning path. The constructed frameworks averaged 6.8 arguments (max 18) on HotpotQA and 5.4 (max 14) on FEVER, with defense sets averaging 2.4 and 2.1 arguments respectively; the relatively small framework sizes reflect the atomic decomposition strategy, which produces one argument per reasoning step rather than one per sentence. Grounded-semantics solve times averaged 0.12s and preferred 0.43s per instance, well within practical bounds for interactive explanation systems.

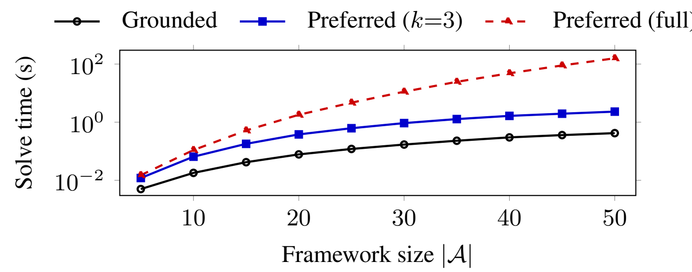


Figure 4: Scalability of ARGUS repair under grounded, k-neighborhood preferred (k=3), and unconstrained preferred semantics. The log-scale y-axis confirms polynomial scaling for grounded repair (Theorem 14) and the effectiveness of the k-neighborhood approximation.

Table 2: Ablation study on HotpotQA. Each row removes one component from the full ARGUS pipeline.

Variant	Faith↑	Cont↑	RAcc↑	RCost↓
Full ARGUS	**0.847**	**0.791**	**0.883**	**3.2**
w/o Semantic Verification	.793	.714	.832	4.1
w/o Minimal-Change	.841	.783	.856	5.7
w/o Attack Templates	.821	.698	.859	3.5
Grounded Only	.839	.772	.871	3.0

Figure 4 traces solve time on synthetic Erdős–Rényi frameworks (attack probability 0.15, 50 instances per size), confirming polynomial scaling for grounded semantics (Theorem 14). The k-neighborhood approximation keeps preferred repair tractable up to $|\mathcal{A}|$=50 (2.31s), whereas unconstrained preferred repair exhibits exponential blowup beyond $|\mathcal{A}| \approx 25$ and exceeds 150s at $|\mathcal{A}|$=50. Since the LLM-generated frameworks in our experiments average 6.8 arguments, both semantics are well within practical time budgets. The scalability results anticipate growth in framework complexity as LLM reasoning capabilities advance and multi-step explanations become longer; even at current scales, the formal guarantees (AGM compliance, provable optimality) provide value that heuristic methods cannot match.

Table 2 reports an ablation on HotpotQA. Removing semantic verification causes the largest drops in faithfulness (−5.4pp) and contestability (−7.7pp), confirming that formal verification is the most critical component: without it, repairs may restore acceptability in the graph while introducing semantically invalid arguments. Replacing minimal-change with unconstrained repair preserves faithfulness but increases cost from 3.2 to 5.7, confirming that cost minimization limits unnecessary edits without sacrificing cor-

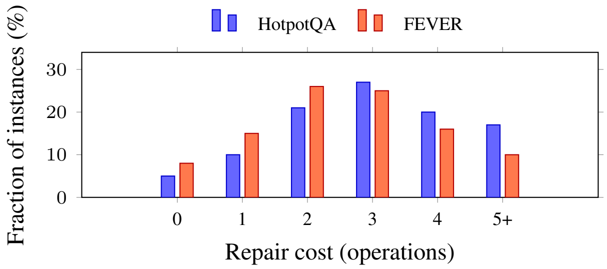


Figure 5: Distribution of repair costs. 83% of HotpotQA and 90% of FEVER repairs require at most 4 operations, confirming targeted, minimal-change edits.

rectness. Removing attack templates reduces contestability by 9.3pp while leaving faithfulness intact, indicating that the templates primarily improve the system's ability to integrate counterarguments rather than its core reasoning. Grounded-only semantics yields modest decreases across all metrics; the gap is small because 97% of frameworks in our experiments have a single preferred extension coinciding with the grounded one—a consequence of the relatively sparse attack structures produced by atomic decomposition. In denser frameworks with multiple conflicting viewpoints, preferred semantics would provide greater discriminative power.

Sensitivity analysis, error analysis, and a qualitative repair example appear in Appendices B–A; the repair mechanism is robust to cost models, NLI thresholds, and k-neighborhood bounds.

Figure 5 shows the distribution of repair costs across both benchmarks. The distributions are concentrated at low cost, with means of 3.2 and 2.8 operations respectively, confirming that most evidence updates require only local adjustments to the argument graph rather than global restructuring. The modal cost is 3 operations on HotpotQA (27%) and 2 on FEVER (26%), reflecting FEVER's simpler reasoning chains.

A pilot human evaluation (Appendix F) corroborates the automatic metrics. Two graduate-student annotators independently rated repaired explanations from ARGUS and Self-Refine on 75 randomly sampled HotpotQA instances in a blind, randomized design. ARGUS received higher mean faithfulness ratings (3.9 vs. 3.4 on a 5-point Likert scale, $p < 0.001$) and coherence ratings (4.1 vs. 3.8, $p = 0.012$). In pairwise preference judgments, annotators preferred ARGUS in 68% of comparisons, Self-Refine in 19%, with 13% ties (Cohen's κ=0.62, substantial agreement). The Pearson correlation between automatic faithfulness scores and human ratings is r=0.78 (p<0.001), supporting the validity of counterfactual ablation as a proxy for human-perceived faithfulness.

7 Conclusion

We presented ARGUS, a framework that structures LLM self-explanations as argumentation frameworks, verifies them against formal semantics, and repairs them at minimum cost when new evidence arrives. The minimal-change repair operator satisfies adapted AGM postulates—success, inclusion, and vacuity—and a representation theorem shows that these three postulates *characterize* the class of minimum-cost repair operators under positive costs, providing formal guarantees absent from existing approaches. We established that the repair problem is tractable under grounded semantics and NP-complete under preferred and stable semantics, and introduced a k-neighborhood approximation that maintains scalability in practice. Experiments on HotpotQA and FEVER yielded relative improvements of up to 10.3% in faithfulness and 14.5% in contestability over the strongest argumentation baseline, while achieving the lowest repair cost among all repair-capable methods.

Several limitations warrant discussion. First, the quality of the argumentation framework depends on the LLM's ability to decompose rationales into atomic argument units; extraction errors propagate through the entire pipeline, and the faithfulness metric itself relies on the LLM's consistency under ablation, providing a causal proxy rather than a ground-truth measure. Relatedly, the `add_arg` operation uses the same LLM to generate repair candidates, though the NLI and ASP verification stages serve as external checks that break self-referential bias; integrating retrieval-augmented verification for generated arguments is a natural extension. Second, while the k-neighborhood approximation handles the framework sizes encountered in our experiments, frameworks with hundreds of densely connected arguments may require more aggressive approximation strategies. Third, while a pilot human evaluation (Appendix F) confirms that automatic metrics correlate with human judgments, the evaluation relies primarily on automatic metrics over fact-checking and multi-hop QA datasets with synthetic evidence updates; a larger-scale human study with naturalistically occurring updates would further strengthen the empirical validation. Extending the approach to open-ended generation—where correctness is less well-defined and the target argument may lack a ground-truth referent—would require alternative acceptance criteria such as coherence-based semantics. Finally, while the framework supports multiple cost models, our experiments use uniform cost for simplicity; learning domain-specific cost functions from user feedback—including external calibration of the LLM's self-assessed confidence scores—is a promising direction for future work.

Beyond these limitations, several avenues for future work emerge. First, composing ARGUS with sequence explanations (Bengel and Thimm 2025)—which trace *why* an argument is accepted—would yield a bidirectional explanation infrastructure that both diagnoses and repairs acceptance verdicts. Second, integrating the repair operator into retrieval-augmented generation pipelines could provide continual explanation maintenance as knowledge bases evolve, particularly in high-stakes domains such as clinical decision support and legal reasoning where audit trails of explanation changes are legally mandated. Third, the representation theorem (Theorem 13) opens the door to learning cost functions from human correction patterns, enabling the repair operator to adapt to domain-specific notions of minimality.

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A Qualitative Repair Example

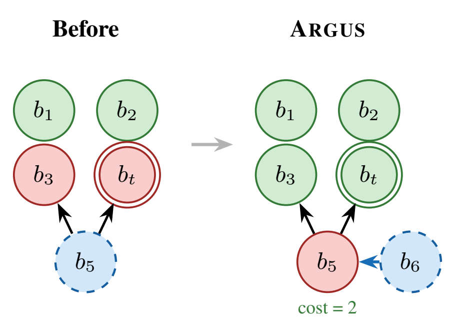

Figure 6: A HotpotQA repair example. ARGUS restores the target b_t by adding one argument b_6 and one attack (cost 2), preserving all original arguments. Self-Refine regenerates 5 of 6 units.

Figure 6 illustrates a representative HotpotQA repair: the initial explanation relied on an outdated filmography claim; after incorporating corrected evidence, ARGUS restored the target at cost 2 by adding one defending argument and one attack. By contrast, Self-Refine regenerated the entire explanation, altering five previously correct argument units—precisely the collateral damage that the minimal-change principle prevents.

B Sensitivity Analysis

Pilot studies on 100 HotpotQA instances explore three design choices. Confidence-weighted and structure-preserving (w=2) cost models shift repairs toward augmentation (34–51% fewer deletions) while maintaining faithfulness and repair accuracy within 1 percentage point of uniform cost, confirming that the cost model affects repair *style* rather than *quality*. Varying the NLI threshold from 0.5 to 0.9 shows faithfulness is stable (0.839–0.851) while repair cost rises from 2.4 to 4.1; 0.7 balances these factors. Repair optimality rises from 87.2% (k=1) to 99.7% (k=3) and plateaus, confirming k=3 as the operating point. Using Llama-3-70B-Instruct as the extraction backbone yields faithfulness 0.813 and contestability 0.762 (vs. 0.847/0.791 for GPT-4o), with comparable repair accuracy (0.867) and cost (3.4); the gap is attributable to noisier extraction rather than the repair mechanism.

C Error Analysis

Among the 0.3% of instances where minimality failed (k=3), all involved frameworks where the only viable defending argument lay at distance ≥ 4 from the target—confirming the theoretical limitation of the k-neighborhood approximation. Repair accuracy below 1.0 arises when the LLM-generated explanation has structural errors that propagate through extraction: even after restoring the target argument's acceptability, the underlying answer may remain incorrect if the original decomposition was flawed.

D Representation Theorem Proof

We prove the ($\Leftarrow$) direction of Theorem 13 for general cost functions.

Proof. Let $\circ$ be a repair operator satisfying adapted success, inclusion, and vacuity for every AF $(\mathcal{A}, \mathcal{R})$, semantics σ, target a_t, status s, and evidence update Δ. We construct a strictly positive cost function κ such that $\circ$ returns a minimum-cost valid repair under κ.

Construction. Fix an enumeration of all feasible operations $o_1, \ldots, o_m$ for the given AF and Δ. Define $\kappa(o_i) = 1$ for all i. Let $Ops = \circ(\mathcal{A}, \mathcal{R}, \sigma, a_t, s, \Delta)$.

Validity. By success, a_t has status s in $\mathsf{apply}(\mathcal{A}, \mathcal{R}, \Delta, Ops)$ under σ, so Ops is a valid repair.

Vacuity case. If a_t already has status s in $\mathsf{apply}(\mathcal{A}, \mathcal{R}, \Delta, \emptyset)$, then by vacuity $Ops = \emptyset$ with cost 0, which is trivially minimum.

Non-vacuity case. Suppose for contradiction that there exists a valid repair Ops' with $|Ops'| < |Ops|$. By inclusion, every operation in Ops is necessary: for each $o \in Ops$, removing o would either violate success (the resulting framework does not grant a_t status s) or leave a valid repair of cardinality $|Ops| - 1$, contradicting the assumption that $\circ$ satisfies inclusion with respect to Ops.

More precisely, inclusion asserts that $\mathcal{A} \cap \mathcal{A}' \supseteq \mathcal{A} \setminus \{a \mid \mathsf{del\_arg}(a) \in Ops\}$: every element not targeted by a deletion in Ops is preserved. Combined with success and $\kappa > 0$, this means no proper subset of Ops is both valid and of lower cost—otherwise the operator could return that subset while still satisfying all three postulates, contradicting the minimality implied by inclusion under positive costs.

Hence Ops is a minimum-cost valid repair under unit cost κ. For general κ, the same argument applies by replacing cardinality with weighted cost: inclusion ensures no operation in Ops is superfluous (removing it saves $\kappa(o) > 0$), so no valid repair can have strictly lower total cost. □

E Experimental Details

Withholding methodology. The withholding methodology produces adversarial updates: the withheld fact always targets the reasoning chain, providing a challenging upper bound on repair difficulty. Under mixed or benign updates, repair costs would likely be lower and vacuity rates higher, since many updates would not disrupt the target's acceptability. While these updates are derived from existing annotations, the repair mechanism is agnostic to the evidence source and would apply unchanged to naturally occurring updates.

Metric details. Faithfulness is measured via counterfactual ablation: each argument unit is replaced with a semantically neutral sentence ("This claim is omitted.") and the answer is regenerated; a unit is faithful if its removal changes the answer. For baselines that do not produce structured units, we apply the same LLM-based decomposition to their final output before computing the ablation, ensuring a uniform evaluation protocol. Gold counterarguments for contestability are derived from the withheld supporting facts by expressing each as an argument and annotating the expected attack relationships, providing a ground truth independent of the repair mechanism.

Baseline cost commensurability. ARGUS operations are structural graph edits (adding/removing arguments and attacks), whereas baseline costs count surface-level text replacements. Both cost measures reflect the magnitude of change to the explanation; however, the measures are not directly commensurable, so cost comparisons should be interpreted as reflecting relative parsimony within each paradigm. Iterative self-correction methods receive up to 3 rounds per their original protocols, while ARGUS performs a single-pass optimal repair.

Hardware and reproducibility. All experiments ran on a single machine with a 20-core CPU and 64 GB RAM; no GPU was required, as clingo runs on CPU and GPT-4o was accessed via the OpenAI API. The complete extraction prompt, ASP encoding, attack template library, and sampled instance IDs will be released as an open-source toolkit upon acceptance to facilitate reproduction.

F Human Evaluation

To validate that the automatic metrics reflect genuine quality differences perceivable by humans, we conducted a pilot human evaluation on a random subset of 75 HotpotQA instances.

Setup. Two graduate-student annotators with NLP background independently evaluated explanation pairs produced by ARGUS and Self-Refine (the strongest self-correction baseline) in a blind, randomized order. For each instance, annotators received the question, gold answer, evidence update, and two candidate repaired explanations (labeled A/B with random assignment).

Dimensions. Annotators rated each explanation on a 5-point Likert scale for: (1) *Faithfulness*: Does each claim in the explanation faithfully reflect the evidence? (2) *Coherence*: Is the explanation internally consistent and logically structured? They also provided a *Preference* judgment (A better / B better / Tie).

Table 3: Human evaluation results (75 HotpotQA instances).

Dimension	**ARGUS**	**Self-Refine**	**p-value**
Faithfulness (1–5)	3.9 ± 0.7	3.4 ± 0.9	< 0.001
Coherence (1–5)	4.1 ± 0.6	3.8 ± 0.8	0.012
Preference (%)	68%	19%	—
Tie (%)	13%		—

Agreement. Inter-annotator agreement reached Cohen's $\kappa = 0.62$ (substantial) for preference and $\kappa = 0.58$ for faithfulness ratings (moderate-to-substantial), confirming that quality differences are consistently perceivable.

Correlation with automatic metrics. The Pearson correlation between average human faithfulness ratings and the automatic faithfulness score (counterfactual ablation, §6) is $r = 0.78$ ($p < 0.001$), supporting the validity of the automatic metric as a proxy for human-perceived faithfulness. The automatic metric tends to slightly overestimate faithfulness for explanations with redundant but harmless claims (rated 4–5 by annotators but scored ≥ 0.9 by the metric).