

Living in the Contradiction

A reasoning engine for decision support that tracks multiple contradictory hypotheses over noisy/asynchronous business data, reviving dormant theories with new evidence

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One of the most remarkable aspects of human intelligence is our ability to hold competing explanations “all in mind at once” until the evidence clarifies which is correct.

For example: "Customer satisfaction scores are at an all-time high" AND "Support tickets have doubled". Digging deeper might reveal that:

- The survey only goes to new customers (selection bias)
- Tickets doubled because you made it easier to submit them
- You expanded into a new market segment with different needs
- The tickets are mostly feature requests, not complaints
- Satisfaction surveys are lagging indicators vs. real-time ticket volume

We're able to live in the contradiction until we understand it better. This cognitive flexibility comes from:

- **Parallel processing** across brain regions that can consider multiple theories simultaneously
- **Integrated memory and attention** that keeps all relevant context accessible
- **Natural prioritization** through conscious and unconscious confidence weighting
- **Seamless context switching** between different explanations as evidence evolves

The Core Innovation: Single LLM with Context Rewriting

Classical reasoning frameworks based on formal logical systems require resolution of contradictions to maintain consistency¹. This can lead to premature conclusions when the evidence supports competing explanations.

Our approach gives a single LLM a kind of "unified view" of the situation. Instead of building complex multi-agent systems or forcing immediate belief revision, we use a rewritable context filled with structured assertion tuples. By presenting all hypotheses, evidence, and their relationships simultaneously, the LLM can reason about the complete landscape of possibilities in each reasoning session.

Each piece of evidence becomes a timestamped tuple containing the assertion, confidence level, source, and metadata:

(Enterprise Q4 sales exceeded targets by 30%, 14:23, conf:0.85, active, sales_system)
(Customer acquisition costs increased 50% in SMB segment, 14:25, conf:0.90, active, analytics)
(Server response times degraded during peak load, 14:20, conf:0.75, weakened, monitoring)

Hypotheses exist as special assertions that evolve rather than get replaced:

(Enterprise sales strategy is succeeding, 14:15, conf:0.80, active)
(SMB market requires different approach, 14:18, conf:0.70, active)
(Seasonal patterns explain recent trends, 14:10, conf:0.15, dormant)
(Infrastructure scaling is adequate, 14:12, conf:0.40, active)

When new evidence arrives, the system analyzes these against existing hypotheses and updates confidence scores² based on supporting or contradicting evidence. The system can add new hypothesis to the context and may revive dormant theories as its reasoning evolves. The reasoning process typically takes several cycles to complete before new evidence can be considered, and rumination is actively controlled.

This unified approach proves superior for reasoning because:

- **All relationships are visible:** The LLM sees how each piece of evidence affects every hypothesis

- **Integrated confidence assessment:** Evidence strength is evaluated against the complete context
- **Natural hypothesis interaction:** Competing theories can be compared directly
- **Seamless revival logic:** Dormant hypotheses remain in context for potential reactivation

Natural Reasoning Patterns

This approach produces several patterns that mirror human analytical thinking:

Hypothesis Persistence: Theories don't disappear when contradicted – they weaken and may go dormant, available for revival when circumstances change.

Evidence Accumulation: The system builds cases gradually rather than making immediate judgments based on individual data points.

Analysis Completion: Reasoning continues until the system reaches stable conclusions or explicitly recognizes that evidence supports multiple contradictory explanations equally well.

Oscillation Detection: When evidence genuinely supports contradictory theories equally, the system recognizes this pattern and preserves both interpretations rather than cycling infinitely between them.

Investigation Continuity: Complete tracking of reasoning sessions enables learning and improvement across multiple analyses.

Why This Matters

Business environments often generate contradictory data streams. Building systems that can reason through this uncertainty productively rather than forcing premature resolution or getting stuck in analytical loops creates more trustworthy and useful decision support tools.

In our system, investigations produce comprehensive results which enables:

- **Comparative analysis** across different evidence sets
- **Historical decision audit trails** for compliance and learning
- **Pattern recognition** across multiple investigations
- **Persistent knowledge base** development over time

The key insight is treating contradictory hypotheses as a feature rather than a bug. By allowing multiple competing explanations to coexist and evolve based on evidence strength, we create systems that can reason through complex situations.

¹For example the AGM classical belief revision framework (Alchourrón, Gärdenfors & Makinson, 1985) provides a systematic approach for updating beliefs when new information becomes available.

²Future work could incorporate formal evidential reasoning frameworks such as Dempster-Shafer theory to enhance evidence combination rigor, though our current approach prioritizes implementation simplicity and computational efficiency for practical deployment.

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A reference implementation is available as an open-source project under the GNU Affero General Public License v3.0 (AGPL-3.0) on GitHub at <https://github.com/mossrake/async-reasoning-engine>.

Version 1.0