Robbie's Razor: Stability Regions Under Nonlinear Recursive Dynamics

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Abstract

Preprint v1.1 established a minimal linear entropy-update model for recursive reasoning systems under bounded resources, yielding a clean stability inequality ($\mu M \geq \lambda C$). While analytically useful, linear dynamics do not capture saturation, feedback, or diminishing returns inherent in real recursive systems.

This paper generalizes the stability analysis to nonlinear entropy dynamics. We show that the convergence boundary derived in the linear case extends to a broader *stability region* under mild monotonicity and boundedness conditions. In nonlinear settings with saturation and feedback terms, preserved structure must still offset recomputation-induced drift. The result is not a single equality condition but a region of bounded entropy trajectories. This strengthens the interpretation of Robbie's Razor as a structural stability constraint rather than a property of a specific linear model.

1 Introduction

Preprint v1.1 demonstrated that under a linear entropy update model,

$$H_{t+1} = H_t + \lambda C - \mu M,$$

recursive convergence occurs when preserved structure offsets recomputation drift. However, real systems exhibit nonlinearities:

- Saturation of memory effectiveness
- Feedback between entropy and drift
- Diminishing returns on compression
- Threshold effects under high recursion depth

The central question is whether the Razor stability condition survives such nonlinear generalization.

2 Nonlinear Entropy Update Model

Let $H_t \in \mathbb{R}_{\geq 0}$ represent representational entropy at recursion step t.

We generalize the update equation to:

$$H_{t+1} = H_t + f(C, H_t) - g(M, H_t), \tag{1}$$

where:

- $f(C, H_t)$ models entropy injection from active computation
- $g(M, H_t)$ models entropy reduction from preserved structure

We assume:

1. f is nonnegative and nondecreasing in C
2. g is nonnegative and nondecreasing in M
3. Both are continuous in H_t
4. g exhibits saturation: $\partial g / \partial H_t \to 0$ as $H_t \to 0$

3 Stability Region

Definition 1 (Stability Region)**.** *The system is stable if the entropy sequence $\{H_t\}$ remains bounded and converges to a finite attractor under iteration of Eq. (1).*

Theorem 1 (Nonlinear Recursive Stability Condition)**.** *Assume Eq. (1) with f and g satisfying the above monotonicity and boundedness conditions. If there exists $\epsilon > 0$ such that for sufficiently large H_t:*

$$g(M, H_t) \geq f(C, H_t) + \epsilon,$$

then H_t is ultimately bounded and convergent to a compact stability region.

Proof. Define the Lyapunov candidate $V(H) = H$. Then:

$$V(H_{t+1}) - V(H_t) = f(C, H_t) - g(M, H_t).$$

If $g(M, H_t) \geq f(C, H_t) + \epsilon$ beyond some threshold, then:

$$V(H_{t+1}) - V(H_t) \leq -\epsilon,$$

implying strict decrease for sufficiently large H_t. Therefore, entropy cannot diverge to infinity and must enter a bounded region. Standard discrete-time Lyapunov arguments imply convergence to a compact attractor set. □

4 From Inequality to Region

In the linear case, stability is governed by:

$$\mu M \geq \lambda C.$$

In the nonlinear case, this becomes:

$$g(M, H) \geq f(C, H)$$

for sufficiently large entropy levels.

Thus, stability is no longer a single equality boundary but a *region* in (C, M, H) space.

5 Saturation and Diminishing Returns

Consider:

$$g(M, H) = \frac{\mu M H}{1 + \alpha H}$$

This models saturation: memory effectiveness diminishes at low entropy but scales under pressure.

Similarly, let:

$$f(C, H) = \lambda C(1 + \beta H)$$

model drift amplification under high entropy.

Even under these nonlinear effects, stability requires that for large H:

$$\mu M > \lambda C \beta / \alpha$$

which reduces to the linear condition under limiting cases.

6 Implications

6.1 Robustness of the Razor

The core structural requirement persists:

Preserved structure must dominate recomputation-induced entropy growth.

6.2 Stability as a Region

Real systems operate within a stability region rather than along a knife-edge boundary. This explains why practical architectures tolerate variability yet still collapse when memory discipline is violated.

6.3 Interpretation

Robbie's Razor is therefore not an artifact of linear modeling. It defines a conserved structural condition under broad nonlinear recursion dynamics.

7 Limitations

This analysis remains abstract and does not claim full characterization of transformer dynamics or biological learning. It establishes structural robustness under mild nonlinear assumptions.

8 Conclusion

Preprint v1.1 demonstrated a linear stability inequality for recursive reasoning systems. This work generalizes the result to nonlinear entropy dynamics and establishes that stability is governed by a bounded region rather than a single equality condition.

Robbie's Razor thus emerges as a structural constraint on recursive intelligence under finite resources, invariant under reasonable nonlinear generalizations.

Code and artifacts

`https://github.com/RobbieRazor/robbies-razor-benchmarks`

References

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