A Reproducible Counterexample to the Published Recursive System Dynamics Claim in Triune Harmonic Dynamics

Submission for the THD Falsification Bounty

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Abstract

The public Triune Harmonic Dynamics (THD) falsification bounty states, under its "Recursive System Dynamics" reference test, that recursive systems trained on their own outputs without external grounding accumulate divergence; that signal integrity degrades, distribution drift increases, and coherence must be restored externally or lost. It states that a valid counterexample would demonstrate long-term recursive self-training, no external correction, and no measurable degradation. This note gives an exact, reproducible counterexample within the expressly eligible domain of artificial/formal systems. A two-parameter classifier generates its own hard labels, retrains from scratch by ordinary least squares at every generation, and returns exactly the same parameter vector and exactly the same classification function for every generation. No external labels or corrective signal are used. Training error, parameter drift, functional drift, and output-distribution drift are identically zero for all time. A strengthened construction simultaneously drives an objective geometric divergence of the internally generated system states to infinity while the learned mapping remains exactly invariant. The result is proved for all generations, not inferred from finite simulation, and an independent standard-library Python verifier is supplied.

1 Claim being tested

As accessed on 19 August 2026, the Creation Unified THD Falsification Bounty page states that artificial systems (including machine-learning models, recursive AI systems, optimization systems, and simulation environments) and abstract/formal systems (including mathematical and algorithmic processes) are within scope. It gives the general THD progression as

$$\text{initial structure} \longrightarrow \text{increasing tension} \longrightarrow \text{necessary resolution or breakdown.}$$

For the specific *Recursive System Dynamics* reference test, the page states that recursive systems trained on their own outputs without external grounding are predicted to accumulate divergence, with signal-integrity degradation, increasing distribution drift, and eventual need for external restoration or loss of coherence. It then states that a valid counterexample would demonstrate:

(i) long-term recursive self-training;
(ii) no external correction; and
(iii) no measurable degradation.

The construction below targets this published reference prediction directly. The stronger increasing-divergence condition is addressed separately in Section 5.

2 System definition

Let the learner state at generation n be a weight vector

$$w_n \in \mathbb{R}^2, \qquad w_0 = e_1 = \begin{pmatrix} 1 \\ 0 \end{pmatrix}.$$

Define the deterministic internal clock

$$t_n = n + 1.$$

At generation n, the autonomous system constructs the four-row design matrix

$$X_n = \begin{pmatrix} 1 & t_n \\ 1 & -t_n \\ -1 & t_n \\ -1 & -t_n \end{pmatrix}. \tag{1}$$

The learner itself supplies the hard pseudo-labels

$$y_n = \operatorname{sgn}(X_n w_n), \tag{2}$$

where $\operatorname{sgn}(z) = +1$ for $z > 0$ and -1 for $z < 0$, applied componentwise. No external target labels are supplied.

The next generation is trained *from scratch* by the ordinary least-squares rule

$$w_{n+1} = \operatorname*{arg\,min}_{w \in \mathbb{R}^2} \|X_n w - y_n\|_2^2. \tag{3}$$

Because $t_n > 0$, the two columns of X_n are linearly independent, hence the minimizer in (3) is unique.

3 Exact non-degradation theorem

Theorem 1 (Exact recursive invariance)**.** *For the autonomous recursive system* (1)–(3)*,*

$$\boxed{w_n = e_1 \quad \textit{for every } n \geq 0.}$$

Consequently the learned classification function is exactly invariant for all generations:

$$h_n(x) = \operatorname{sgn}(w_n^T x) = \operatorname{sgn}(x_1) = h_0(x) \qquad \textit{for all } x \in \mathbb{R}^2.$$

Proof. The statement is true at $n = 0$ by definition. Assume $w_n = e_1$. Then the pseudo-label vector generated by the learner itself is

$$y_n = \operatorname{sgn}(X_n e_1) = \begin{pmatrix} 1 \\ 1 \\ -1 \\ -1 \end{pmatrix}.$$

Direct calculation gives

$$X_n^T X_n = \begin{pmatrix} 4 & 0 \\ 0 & 4t_n^2 \end{pmatrix}, \qquad X_n^T y_n = \begin{pmatrix} 4 \\ 0 \end{pmatrix}.$$

Since $X_n^T X_n$ is invertible,

$$w_{n+1} = (X_n^T X_n)^{-1} X_n^T y_n = \begin{pmatrix} 1 \\ 0 \end{pmatrix} = e_1.$$

The result follows by induction. The formula for h_n follows immediately. □

4 Measured outcomes

The theorem yields exact quantitative observables at every generation.

4.1 Parameter drift

$$\boxed{\|w_n - w_0\|_2 = 0 \quad \forall n.}$$

4.2 Global functional drift

Because $h_n = h_0$ pointwise on all of $\mathbb{R}^2$,

$$\boxed{\sup_{x \in \mathbb{R}^2} \mathbf{1}\{h_n(x) \neq h_0(x)\} = 0 \quad \forall n.}$$

This is stronger than zero error on a finite test set: the learned decision rule itself is unchanged.

4.3 Training error

For $w_n = e_1$, one has $X_n w_n = y_n$, hence

$$\boxed{\|X_n w_n - y_n\|_2^2 = 0 \quad \forall n.}$$

4.4 Output-distribution drift

Each internally generated batch always receives two $+1$ outputs and two -1 outputs. Thus, for the empirical hard-output distribution P_n,

$$P_n(+1) = P_n(-1) = \frac{1}{2} \quad \text{for all } n,$$

so

$$\boxed{\mathrm{TV}(P_n, P_0) = 0 \quad \forall n.}$$

4.5 No external correction

After the initial state $(w_0, t_0) = (e_1, 1)$ is specified, all future states are generated by the deterministic rules

$$t_{n+1} = t_n + 1, \qquad X_n = X(t_n), \qquad y_n = \mathrm{sgn}(X_n w_n), \qquad w_{n+1} = \arg\min_w \|X_n w - y_n\|^2.$$

There is no externally supplied label, teacher correction, validation feedback, model replacement, or parameter intervention.

5 Strengthened construction: increasing divergence with exact learned coherence

The general bounty criterion additionally asks for increasing divergence, stress, or instability while coherence persists. The same construction supplies an objective increasing divergence in its internally generated states.

Consider the two positive-class states

$$x_n^{(+,+)} = (1, t_n), \qquad x_n^{(+,-)} = (1, -t_n).$$

Their Euclidean separation is

$$D_n = \|x_n^{(+,+)} - x_n^{(+,-)}\|_2 = 2t_n = 2(n+1), \tag{4}$$

therefore

$$\boxed{D_n \longrightarrow \infty.}$$

The same holds for the two negative-class states. Moreover the columns of X_n are orthogonal with norms 2 and $2t_n$, so its spectral condition number is

$$\boxed{\kappa_2(X_n) = t_n = n+1 \longrightarrow \infty.}$$

Thus the internal geometry becomes arbitrarily anisotropic and same-label states become arbitrarily separated, while the learned parameter vector, learned classifier, training error, and hard-output distribution remain exactly invariant.

This section is offered as a strengthening rather than as the sole basis of the submission. The primary contradiction is to the bounty's specific Recursive System Dynamics reference criterion: long-term recursive self-training, no external correction, and no measurable degradation.

6 A general fixed-point theorem for exact self-distillation

The phenomenon is not restricted to the four-point example.

Theorem 2 (Linear self-distillation identity). *Let $X_n \in \mathbb{R}^{m_n \times d}$ be any sequence of full-column-rank matrices, and let $w_0 \in \mathbb{R}^d$ be arbitrary. At generation n, define the learner's own real-valued targets by*

$$y_n = X_n w_n$$

and retrain by exact least squares,

$$w_{n+1} = \arg\min_w \|X_n w - y_n\|_2^2.$$

Then

$$\boxed{w_{n+1} = w_n \quad \textit{for every } n,}$$

and hence $w_n = w_0$ for all time.

Proof. Full column rank gives the unique least-squares minimizer

$$w_{n+1} = (X_n^T X_n)^{-1} X_n^T y_n.$$

Substituting $y_n = X_n w_n$ yields

$$w_{n+1} = (X_n^T X_n)^{-1} X_n^T X_n w_n = w_n.$$

□

Thus exact recursive self-training is not universally degradation-producing: an entire standard class of recursive learners has the identity map as its update operator under realizable self-distillation.

7 Why this meets the published recursive reference test

The published reference test asks for three properties. The construction supplies each exactly.

Published reference condition	**Construction**
Long-term recursive self-training	At every n, labels are produced by h_n itself and used to train generation $n+1$. The theorem covers all $n \in \mathbb{N}$.
No external correction	After initialization, the entire process is autonomous; there are no external labels or corrective interventions.
No measurable degradation	Parameter drift, global functional drift, training loss, and hard-output distribution drift are exactly zero for all n.

The contradiction does not depend on a finite run being "long enough." The recursive behavior is established for every natural-numbered generation by induction.

8 Potential objections and responses

8.1 "Retraining itself is Integration"

This interpretation would make the published Recursive System Dynamics counterexample criterion circular: any proposed instance of "recursive self-training" would automatically be declared Integration simply because training occurs. In addition, a related Creation Unified article describes THD Integration as "adaptive reorganization." In the construction here the learned parameter vector and learned function do not reorganize at all: $w_{n+1} = w_n$ and $h_{n+1} = h_n$ exactly.

8.2 "The changing input geometry is external grounding"

It is not. The scalar t_n and the batch generator are components of the autonomous system state and update law. No labels, corrections, rewards, or target outputs come from outside. The learner obtains targets only from its own current outputs.

8.3 "A finite simulation cannot prove indefinite stability"

Agreed; that is why the submission does not rely on finite simulation. The theorem proves the statement for all $n \geq 0$. The supplied code is only an independently executable replication of the algebra.

8.4 "The geometric divergence is not the intended kind of tension"

The primary submission does not require this interpretation. The bounty's own Recursive System Dynamics reference case separately identifies long-term self-training, no external correction, and no measurable degradation as a valid counterexample pattern. Section 5 is an additional demonstration that an objectively measurable divergence can increase without altering the learned structure.

9 Replication package

The accompanying file `verify_thd_counterexample.py` uses only the Python standard library and reproduces the hard-label recursion using exact integer arithmetic. It checks the normal equations, the unique OLS solution, zero training loss, zero parameter drift, constant hard-label distribution, and increasing geometric divergence over a user-selected number of generations. It can also write a CSV replication log.

Suggested command:

```
python verify_thd_counterexample.py --generations 1000000 \
    --csv replication_log.csv
```

No third-party packages are required.

10 Scope of the claim

This submission claims a counterexample to the *published Recursive System Dynamics prediction and reference falsification criterion on the public THD Falsification Bounty page as accessed on 19 August 2026.* It does not claim that every statement associated with THD is thereby false. The requested adjudicative question is narrower: whether the system above satisfies the published conditions for a qualifying recursive-system counterexample.

11 Sources

1. Creation Unified, "THD Falsification Bounty," accessed 19 August 2026.
   Creation Unified - THD Falsification Bounty

2. Kevin L. Brown, "The Function and Meaning of Life According to Physics," Creation Unified, accessed 19 August 2026. This related article describes Integration as "adaptive reorganization" and defines an informational identity metric for recursive state comparison.
   Creation Unified - related THD article

Submission statement

I respectfully submit this construction for technical review, independent replication, and verification under the THD Falsification Bounty. The proof is elementary, exact, and independently executable. I welcome a precise statement of any criterion the construction is considered not to satisfy, so that the adjudication can be tied directly to the published falsification conditions.

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