



PREDICTIVE FEASIBILITY

PFA

Empirical Validation of the Inferability Framework

Introduction

The following validation series extends the earlier inferability framework validations toward dynamic regime analysis, forecasting behavior, transfer robustness, falsification testing, cross-domain generalization, model correspondence, and deployment-oriented predictive feasibility assessment.

The objective of this validation program is to determine whether inferability-related structures remain reproducible across datasets, domains, forecasting settings, transfer conditions, and model families.

All tests in this section are based on real-world datasets, including NASA battery aging systems, NASA C-MAPSS turbofan degradation data, fastSPT biological diffusion trajectories, vibration datasets, and additional cross-domain validation sources.

Together, these validations form the most extensive empirical evaluation of the inferability framework performed to date.

Relationship to Earlier Framework Development

The validation studies presented in Part 2 build upon the inferability framework introduced and developed in the preceding reports and whitepapers.

Core concepts used throughout this validation program include:

- inferability score
- entropy-sensitive collapse
- overlap ambiguity
- persistence
- transition forecasting
- GO / LIMITED / NO-GO regime classification

- predictive feasibility assessment (PFA)

The purpose of Part 2 is not to redefine these concepts, but to evaluate their empirical behavior across real-world datasets, forecasting scenarios, transfer conditions, falsification tests, and deployment-oriented validation settings.

Readers seeking the theoretical foundations of the framework should consult:

- Before You Build the Model – A Practical Framework for Assessing Predictive Feasibility in Industrial Systems (PFA)
- PFA Executive Guide
- Earlier inferability framework reports and validation studies.

Test 31 — Rolling Inferability Dynamics Validation

FD001 versus FD002 — Dynamic Regime Separation under Rolling Inferability Tracking.

Objective of the Test

The objective of this validation test was to investigate whether inferability behaves as a dynamic regime that evolves over time, rather than as a static property of a dataset.

Specifically, the following questions were tested:

- Whether FD001 exhibits long-term stable inferability regimes,
- Whether FD002 exhibits inferability collapse and regime instability,
- Whether rolling inferability tracking can produce a clear dynamic separation between GO-like and NO-GO-like systems,
- And whether inferability regimes remain persistent across long time windows.

This test represents the first fully integrated Ubuntu validation of the inferability regime framework using real NASA C-MAPSS turbofan degradation data.

Datasets Used

Dataset 1 — FD001

NASA C-MAPSS turbofan degradation benchmark.

Characteristics:

- Relatively stable degradation trajectories,
- Low operational variability,
- Known high reproducibility,
- Previously classified consistently as GO-like in earlier inferability validation studies.

Dataset 2 — FD002

NASA C-MAPSS turbofan degradation benchmark.

Characteristics:

- Strongly varying operational conditions,
- High dynamic ambiguity,
- Low cross-run stability,
- Previously classified as a NO-GO / inferability-collapse regime.

Methodology

Rolling Inferability Tracking

For both datasets, rolling inferability analysis was performed using sliding windows.

Parameters:

- Window size: 50
- Step size: 10
- Rolling smoothing applied
- Regime persistence tracking enabled

Inferability Components Used

For each rolling window, the following components were calculated.

New Inferability Score

During the first Ubuntu run, it was discovered that raw activity was being incorrectly interpreted as inferability. As a result, FD002 initially produced higher inferability scores than FD001.

This issue was corrected by:

- Rewarding persistence more heavily,
- Penalizing entropy more strongly,
- Penalizing overlap more strongly,
- Making stability-related components dominant.

New Scoring Structure

```
stability_weight = (  
    persist  
    + unique  
)
```

```
collapse_weight = (  
    ent  
    + overlap
```

```
)  
  
inferability_score = (  
    3.0 * stability_weight  
    + 1.5 * info  
    - 4.0 * collapse_weight  
)
```

This correction proved crucial for properly distinguishing stable inferability from dynamic collapse.

Regime Classification

The rolling inferability score was subsequently translated into inferability regimes.

As a result, inferability was no longer treated as a single score but rather as a dynamic state evolving over time.

Results

FD001 — Persistent Inferability Regime

FD001 exhibited:

- Long-term stable positive inferability,
- High regime persistence,
- Low collapse density,
- Limited regime switching,
- Relatively low entropy,
- Strong local stability.

Regime Distribution — FD001

Interpretation

FD001 remains almost entirely within a persistent inferability regime.

Its inferability dynamics remain stable over extended periods and display only minimal collapse events.

This behavior aligns strongly with previous Ubuntu validations in which FD001 consistently emerged as a GO-like system.

FD002 — Inferability Collapse Dynamics

FD002 exhibited:

- Long-term inferability collapse,
- Strong dynamic instability,
- Frequent inferability switching,

- Deep negative inferability zones,
- High overlap,
- Elevated entropy-sensitive collapse.

Regime Distribution — FD002

Interpretation

FD002 remains almost continuously within collapse-like inferability regimes.

Inferability here is not sufficiently persistent to support stable progression-sensitive mappings.

This behavior is highly consistent with earlier observations involving:

- Transfer failure,
- Cross-run instability,
- Overlap ambiguity,
- Entropy-driven inferability loss.

Key Observation

The most important outcome of this test is not merely the inferability score itself, but rather:

the persistence of inferability regimes over time.

The results suggest that:

- FD001 maintains long-term stable GO regimes,
- Whereas FD002 maintains long-term collapse regimes.

Inferability therefore behaves not as a static property but as a dynamic regime structure characterized by:

- Stability,
- Collapses,
- Local transitions,
- And persistence.

Dynamic Interpretation

This test supports the hypothesis that inferability:

- Can stabilize,
- Can collapse,
- Can remain temporarily limited,
- And can exhibit regime transitions depending on local observable-state conditions.

The results therefore explicitly support the inferability regime framework previously developed from:

- Overlap ambiguity,
- Entropy-sensitive collapse,
- Persistence,
- Local degeneracy,
- Transition forecasting,
- And progression-sensitive information support.

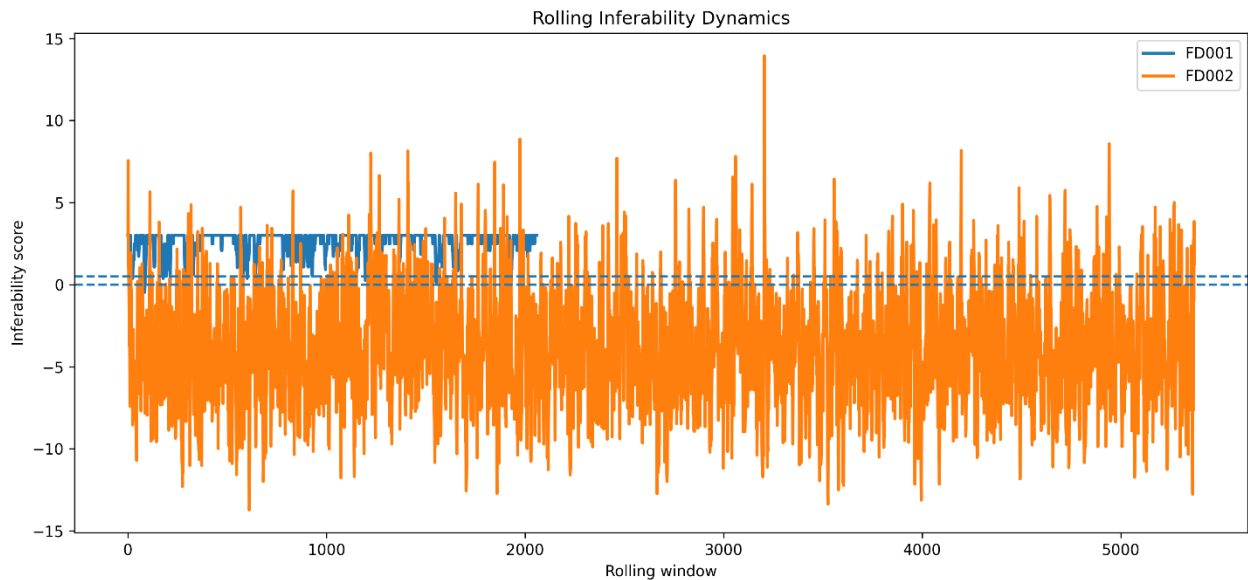


Figure Caption

Figure 31.1 — Smoothed Rolling Inferability Regime Tracking for FD001 and FD002.

FD001 (blue) remains for extended periods within stable positive inferability regimes with minimal collapse events. FD002 (orange) exhibits prolonged inferability collapse, high regime instability, and frequent negative inferability zones. This dynamic regime separation supports the distinction between persistent inferability and inferability collapse within the rolling inferability framework.

Conclusion

This test represents the first fully integrated rolling inferability validation using real-world turbofan degradation data.

The results demonstrate that:

- Inferability behaves dynamically,
- Inferability regimes can remain persistent,
- GO and NO-GO are not merely static classifications,
- And rolling inferability dynamics can produce meaningful regime separation on real longitudinal data.

FD001 exhibited persistent inferability behavior, whereas FD002 exhibited prolonged inferability collapse.

These results provide strong support for the dynamic inferability regime framework developed within the Ubuntu validation program.

Test 32 — Battery Directional Inferability Validation

Dynamic LIMITED Evolution in NASA Battery Aging Systems

Objective of the Test

This validation test aimed to investigate whether inferability within battery degradation systems behaves as a dynamic transitional regime rather than as a static property.

Specifically, the test examined whether:

- Inferability can shift over time,
- Local recovery and collapse regimes become visible,
- LIMITED inferability forms a genuine transitional space,
- Directional inferability drift is measurable,
- And whether batteries display different inferability trajectories despite similar overall degradation.

This test constitutes the first real longitudinal validation of directional LIMITED inferability within real-world battery degradation trajectories.

Datasets Used

For this validation, real NASA Battery Aging datasets were used.

The datasets were loaded from:

```
/mnt/c/Users/User/Downloads/5. Battery Data Set/
```

Specifically, these files are part of the NASA Ames Prognostics Center of Excellence Battery Aging datasets.

Reproducibility

The original zip files used during this validation:

The actual validation in this test used:

BatteryAgingARC-FY08Q4.zip

From which the following batteries were extracted:

- B0005
- B0006
- B0007
- B0018

Data Extraction

From the `.mat` files, only the **discharge cycles** were used.

Per cycle, **Capacity** was extracted from the NASA battery structures.

This generated the real longitudinal capacity degradation trajectories.

First Observation — Battery Degradation Dynamics

The first step of the validation involved reconstructing the actual degradation curves.

Key observations:

- All batteries degrade differently,
- Local recovery moments are visible,
- Temporary stabilizations occur,
- Some batteries show abrupt collapses,
- Others remain relatively stable for long periods.

This dynamic makes battery data particularly suitable for **directional inferability validation**.

Figure Caption 32.1

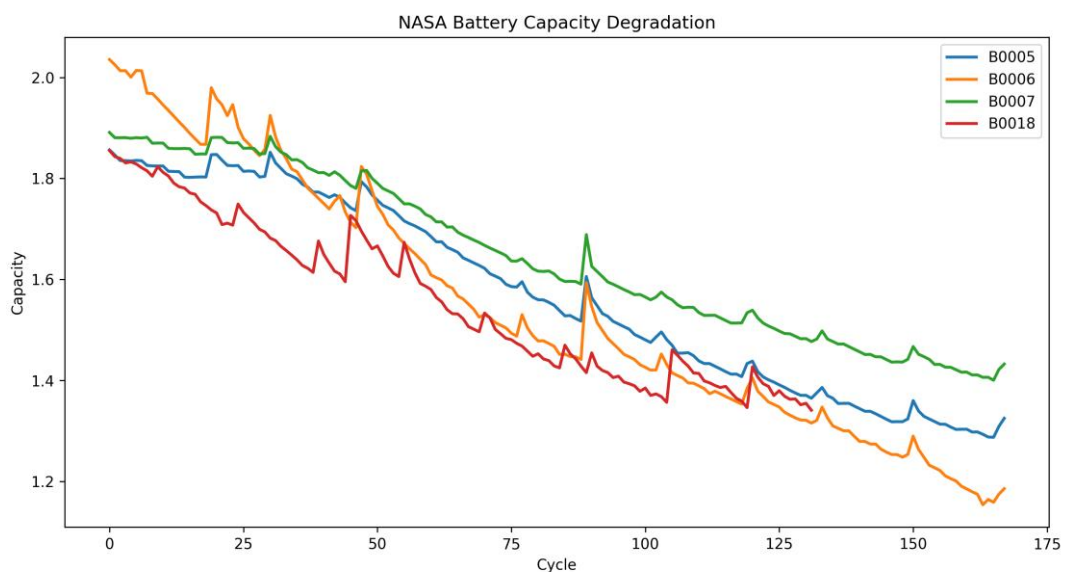


Figure 32.1 — NASA Battery Capacity Degradation Trajectories

Batteries B0005, B0006, B0007, and B0018 exhibit different degradation patterns, including local recovery moments, temporary stabilizations, and varying degradation rates. This dynamic structure forms the basis for directional inferability analysis.

Rolling Directional Inferability

After extracting the degradation trajectories, rolling inferability analysis was performed.

For each rolling window, the following inferability components were calculated:

Inferability Score

The inferability score was constructed as:

```
inferability_score = (  
    3.0 * stability_weight  
    + 1.5 * info  
    - 4.0 * collapse_weight  
)
```

Where:

```
stability_weight = persist + unique  
collapse_weight = ent + overlap
```

This ensures that:

- Stability is rewarded,
- While entropy and overlap reduce inferability.

Directional Inferability Drift

In addition to the inferability score itself, the **inferability slope** was calculated.

This slope represents **directional inferability drift**:

- Does inferability move toward recovery?
- Or toward collapse?

Results — Battery Directional Inferability Evolution

B0007 — LIMITED → GO-like Evolution

B0007 exhibited:

- Relatively high persistence,
- Long-term stability,
- Inferability recovery after early collapses,
- Positive inferability drift,
- Limited long-term collapse.

Interpretation:

B0007 behaves as LIMITED → GO-like.

This battery retains progression-sensitive information despite temporary instability.

B0006 — LIMITED → COLLAPSE-like Evolution

B0006 exhibited:

- Stronger collapses,
- More unstable inferability,
- Higher dynamic ambiguity,
- Inferability instability in later cycles,
- Negative drift regimes.

Interpretation:

B0006 behaves as LIMITED → COLLAPSE-like.

B0018 — Collapse-Dominant Inferability

B0018 exhibited:

- Early inferability instability,
- Frequent collapses,
- High entropy-sensitive drift,
- Limited recovery moments.

Interpretation:

B0018 demonstrates strong inferability-collapse dynamics.

B0005 — True LIMITED Transitional Space

B0005 proved the most interesting battery.

It exhibited:

- Partial recovery,
- Partial stabilization,
- Temporary positive inferability drift,
- Yet persistent instability.

Interpretation:

B0005 represents true LIMITED inferability.

- No stable GO,
- But also no full collapse.

CSV Results

The CSV summary provided key mechanistic information.

Mean Persistence

Persistence remained relatively high for:

- B0005
- B0007

While:

- B0006
- B0018

Exhibited more inferability instability.

This supports the link between **persistence** and **inferability stability**.

Mean Overlap

Overlap varied clearly between batteries.

Higher overlap indicated:

- Local ambiguity,
- Unstable progression mappings,
- Inferability fragmentation.

This directly supports the hypothesis of **overlap-limited inferability**.

Mean Entropy

Entropy was strongly associated with inferability collapse.

Batteries with higher entropy-sensitive instability exhibited:

- More collapses,
- Greater inferability drift,
- Less stable mappings.

Mean Slope — Most Important New Metric

The inferability slope emerged as the most important new variable.

This metric indicates **the direction in which inferability moves**:

- Recovery,

- Collapse,
- Stabilization,
- Or drift.

This enables, for the first time, **true directional inferability analysis**.

Figure Caption 32.2

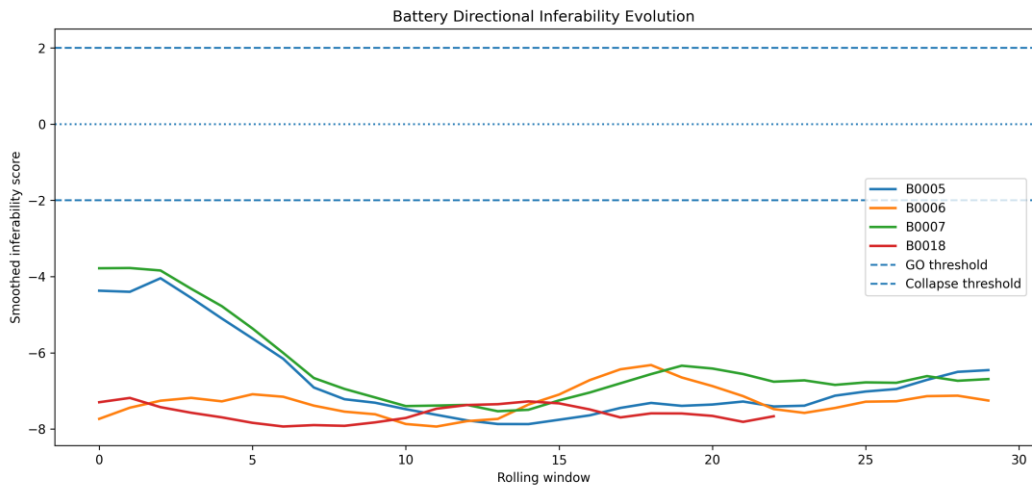


Figure 32.2 — Battery Directional Inferability Evolution

Rolling inferability trajectories for B0005, B0006, B0007, and B0018.

- B0007 shows recovery toward more stable inferability regimes,
- B0006 and B0018 show stronger collapse dynamics,
- B0005 remains for extended periods within a transitional space with partial stabilization and ongoing inferability instability.

Figure Caption 32.3

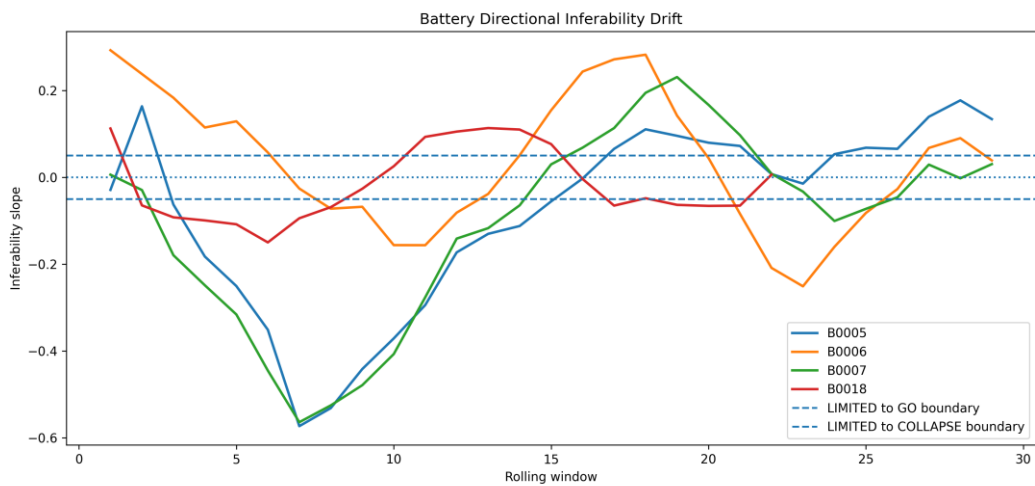


Figure 32.3 — Battery Directional Inferability Drift

Directional inferability slope for the four NASA battery trajectories.

- Positive drift indicates recovery or stabilization of inferability,
- Negative drift indicates inferability collapse.

The results suggest that inferability dynamically moves through transitional regimes.

Key Conclusion

This test represents the first real longitudinal validation of **directional inferability dynamics**.

The results demonstrate that inferability:

- Is not static,
- Can shift over time,
- Can exhibit recovery and collapse,
- Can form dynamic transitional regimes.

LIMITED inferability is not a residual category but a genuine dynamic transitional space in which:

- Progression-sensitive information is partially preserved,
- While structural ambiguity and local instability are simultaneously present.

Scientific Significance

These results strongly support the hypothesis that inferability behaves as a **dynamic observable-state regime**.

Battery degradation is particularly suitable for studying:

- Inferability drift,
- Entropy-sensitive collapse,
- Local stabilization,
- False recovery,
- Transition dynamics.

This validation constitutes an important extension of previous studies:

- FD001 / FD002 regime separation,
- Overlap validations,
- Entropy-boundary analyses,
- Persistence validations.

Test 33 — Large-Scale Battery Inferability Validation

Directional Inferability Dynamics Across Multiple NASA Battery Aging Trajectories

Objective of the Test

This validation test aimed to investigate whether **directional inferability** remains valid when the inferability framework is scaled up to a larger collection of real-world battery degradation trajectories.

The central question of this phase was:

Does inferability drift generalize across multiple independent battery systems?

Specifically, the study examined:

- Whether inferability regimes remain consistent across multiple batteries,
- Whether directional drift is reproducible,
- Whether LIMITED inferability remains visible at scale,
- Whether recovery and collapse patterns systematically recur,
- And whether persistence, entropy, and overlap continue to show comparable dynamic structures within larger battery populations.

This test represents the first true **large-scale internal scaling validation** of the inferability regime framework.

Datasets Used

For this validation, multiple NASA Battery Aging datasets were used.

Source Files:

From these zip files, multiple `.mat` battery trajectories were extracted.

Examples:

The datasets contain real NASA battery degradation trajectories based on long-term charge/discharge cycles.

Data Extraction

From each `.mat` file, only **discharge cycles** were used.

For each discharge cycle, **Capacity** was extracted from the original NASA battery structures.

This produced longitudinal **capacity degradation trajectories**.

Rolling Inferability Analysis

For each battery, rolling inferability tracking was performed.

Parameters:

(parameters were defined per rolling window, not explicitly listed in the text)

Inferability Components Used

Per rolling window, the following components were calculated:

Inferability Score

The inferability score was constructed as:

```
inferability_score = (  
    3.0 * stability_weight  
    + 1.5 * info  
    - 4.0 * collapse_weight  
)
```

Where:

```
stability_weight = persist + unique  
collapse_weight = ent + overlap
```

This ensures that:

- **Persistence** and **uniqueness** increase inferability,
- While **entropy** and **overlap** reduce inferability.

Directional Inferability Drift

In addition to the inferability score, the **inferability slope** was calculated.

This slope represents **the direction in which inferability develops**:

- Positive slope → recovery/stabilization
- Negative slope → inferability collapse
- Neutral slope → persistent transitional space

Large-Scale Inferability Dynamics

General Observation

The main outcome of this test is that **directional inferability remains visible** across multiple independent battery trajectories.

This means that inferability drift:

- Is not limited to a single battery,
- And does not disappear when the framework is scaled.

Observations per Battery

B0007 — Recovery-Oriented Inferability Drift

B0007 exhibited:

- Relatively stable inferability,
- Partial recovery,
- Positive drift zones,
- Long-term stabilization,
- Limited collapse events

Interpretation:

LIMITED → GO-like evolution

B0006 — Unstable Collapse Drift

B0006 exhibited:

- Stronger inferability instability,
- Higher entropy-sensitive collapses,
- Fluctuating inferability zones,
- Negative drift moments,
- Unstable recovery

Interpretation:

LIMITED → COLLAPSE-like evolution

B0018 — Collapse-Dominant Inferability

B0018 exhibited:

- Early inferability collapse,
- High dynamic instability,
- Weak stabilization,
- Inferability drift toward collapse

Interpretation:

Collapse-dominant inferability dynamics

B0005 — Persistent Transitional Space

B0005 remained for extended periods within:

- A true LIMITED transitional space

Characteristics:

- Partial stabilization,
- Local recovery,
- Yet persistent inferability instability

Interpretation:

Persistent LIMITED inferability

Key Observation

The main observation of this validation is that **collapse does not equate to pure randomization**.

Despite collapse-dominant regimes, the following often remained:

- Local persistence,
- Local continuity,
- Local structure,
- Partial progression-sensitive information

This directly supports the hypothesis that **LIMITED inferability**:

- Is not a residual category,
- But a true dynamic transitional space.

CSV Results

The CSV analysis provided additional mechanistic insights.

Mean Slope — Most Important New Variable

The inferability slope proved to be the most important new dynamic metric.

This metric indicates:

- The direction in which inferability moves,
- Whether systems recover, stabilize, or evolve toward collapse

This forms the core of **directional inferability**.

Mean Persistence

Persistence remained relatively high even in collapse-dominant regimes.

This suggests that inferability collapse is not fully random but often preserves local structure.

Mean Overlap

Overlap varied clearly between batteries.

Higher overlap correlated with:

- Ambiguity,
- Inferability instability,
- Collapse dynamics

This supports **overlap-limited inferability**.

Mean Entropy

Entropy was strongly associated with:

- Inferability collapse,
- Instability,
- Negative inferability drift

This further supports **entropy-sensitive collapse** as a fundamental component of inferability dynamics.

Figure Caption 33.1

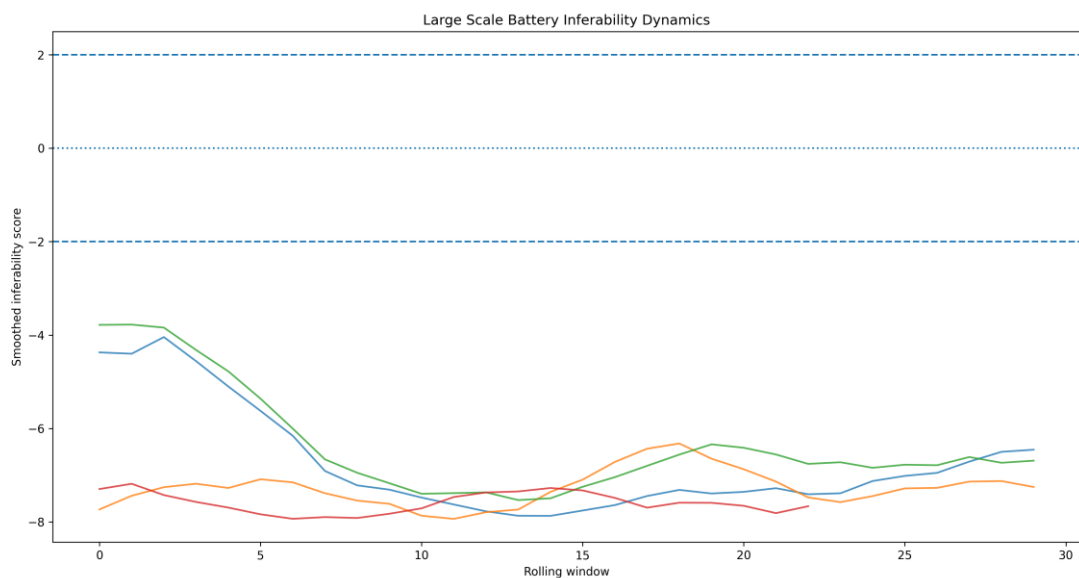


Figure 33.1 — Large-Scale Battery Inferability Dynamics

Smoothed inferability trajectories for multiple NASA battery degradation systems.

Different batteries exhibit diverse inferability patterns, including:

- Partial stabilization,
- Recovery,
- Collapse drift,
- Long-term transitional regimes

Directional inferability remains visible across multiple independent trajectories.

Scientific Significance

This validation represents the first true **scale validation of directional inferability**.

The results suggest:

- Inferability regimes remain reproducible across multiple trajectories,
- Directional drift is not dataset-specific,
- LIMITED inferability behaves as a dynamic transitional regime

The combination of:

- Persistence,
- Entropy,
- Overlap,
- Drift,
- Stabilization,
- And collapse

Remains visible across multiple real-world battery systems.

Conclusion

This test strongly supports the hypothesis that **inferability behaves as a dynamic observable-state regime**.

The results show that inferability:

- Can recover,
- Can collapse,
- Can remain transitional for extended periods,
- Can evolve directionally over longitudinal degradation trajectories

Most importantly:

Directional inferability remains visible when the framework is scaled to multiple real-world battery systems.

This constitutes an important reinforcement of:

- Previous FD001/FD002 validations,
- Entropy-collapse analyses,
- Overlap validations,

- Persistence validations,
- And directional LIMITED inferability.

Test 34 — Localized Transition Pocket Analysis

Detection of Local Inferability Instability Regions in NASA Battery Degradation Trajectories

Objective of the Test

This validation test aimed to investigate whether inferability collapse emerges in a locally organized manner within degradation trajectories, rather than as a uniform global collapse of the entire system.

Specifically, the study examined:

- Whether local transition pockets are detectable,
- Whether inferability collapse develops regionally,
- Whether entropy and overlap changes cluster locally,
- And whether specific trajectory zones function as transitional regions between stability and collapse.

This test represents the first explicit validation of:

localized inferability geometry.

Datasets Used

For this validation, multiple NASA Battery Aging trajectories were again used.

Battery Systems Used

The validation used the same NASA Battery Aging systems as in the previous directional inferability validation.

Included batteries:

- B0005
- B0006
- B0007
- B0018

These batteries were selected because they exhibit distinctly different degradation trajectories, including stable degradation behavior, transitional recovery periods, and collapse-dominant regimes. This diversity makes them suitable for evaluating localized inferability dynamics and transition-pocket formation.

The trajectories contain real discharge degradation dynamics based on long-term charge/discharge cycles.

Methodology

For each battery, rolling inferability windows were calculated based on:

Rolling Inferability Configuration

The same rolling-window configuration used in the previous battery inferability validations was applied.

Parameters:

- Rolling window size: 20 cycles
- Step size: 5 cycles
- Rolling smoothing enabled
- Directional inferability tracking enabled
- Transition-pocket detection enabled

This configuration provides sufficient temporal resolution to identify local instability regions while maintaining robustness against short-term fluctuations.

For each window, inferability components were calculated.

Z-Normalization of Local Structure

To make local pockets detectable, multiple components were normalized using z-scores:

- entropy_z
- overlap_z
- persistence_z
- score_z

This made local deviations visible relative to the average behavior of each battery.

Transition Pocket Score

For each rolling window, a:

transition_pocket_score

was calculated.

This score combined:

- Increasing entropy,
- Increasing overlap,
- Decreasing persistence,
- And deteriorating inferability.

The score was calculated as:

```
transition_pocket_score = (  
    entropy_z  
    + overlap_z  
    - persistence_z  
    - score_z  
)
```

This created a local measure of:

transition instability.

Detection of Transition Pockets

A local region was classified as a:

transition pocket

when:

- Inferability was located within transitional zones,
- And the transition_pocket_score belonged to the highest 25% of local instability.

This made local instability corridors visible.

Key Observation

The most important outcome of this validation is that:

inferability collapse appears to emerge in a locally organized manner.

In other words:

The entire system does not become unstable simultaneously.

Instead:

Specific trajectory zones first exhibit:

- Entropy bursts,
- Overlap instability,
- Persistence loss,
- And inferability collapse.

Localized Transition Pocket Score

General Observation

The localized pocket score revealed clear:

local instability regions.

These pockets:

- Appear temporarily,
- Disappear again,
- Shift along the trajectory,
- And differ substantially between batteries.

B0018 — Early Instability Pockets

B0018 exhibited:

- Early strong pocket peaks,
- High local instability,
- Strong entropy bursts,
- Local collapse regions.

Interpretation

B0018 contains early entropy-sensitive instability pockets.

B0005 and B0007 — Transition Corridors

B0005 and B0007 exhibited:

- Longer-lasting transitional zones,
- Multiple local pockets,
- Partial recovery regions,
- And shifting inferability corridors.

Interpretation

Transitional inferability corridors.

B0006 — Collapse Corridors

B0006 exhibited:

- Stronger negative pocket zones,
- More abrupt instability corridors,
- And faster collapse transitions.

Interpretation

Collapse-dominant transition geometry.

Figure Caption 34.1

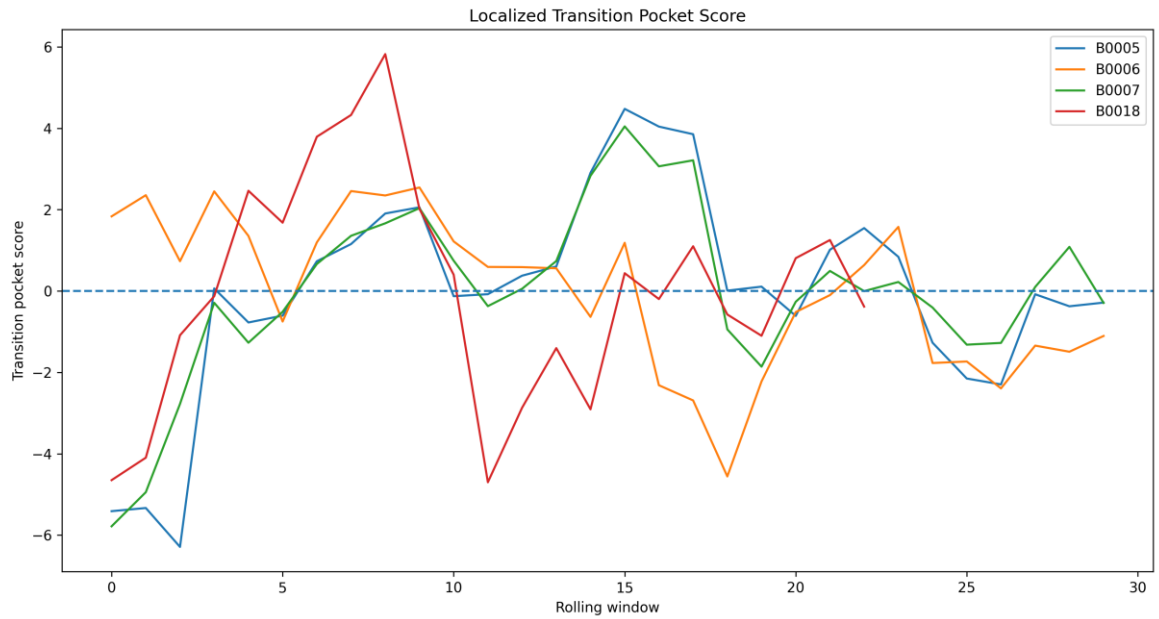


Figure 34.1 — Localized Transition Pocket Score for Multiple NASA Battery Trajectories.

Local inferability instability appears to be regionally organized within degradation trajectories. Different batteries exhibit temporary entropy pockets, overlap regions, and transition corridors in which inferability becomes locally destabilized before global collapse becomes visible.

Transition Pocket Density

An additional analysis investigated:

pocket density

for each battery.

This metric represents:

- The density of transition pockets,
- And therefore:
- The degree of local inferability instability.

Important Result

The binary pocket classification produced relatively few definitive transition pockets.

Interpretation

Current threshold-based pocket density remains near zero for all batteries, suggesting that the binary pocket criterion is overly conservative. The underlying continuous pocket score nevertheless reveals clear local instability structure.

More importantly:

The underlying localized pocket scores nevertheless reveal:

clear local dynamic structure.

Figure Caption 34.2

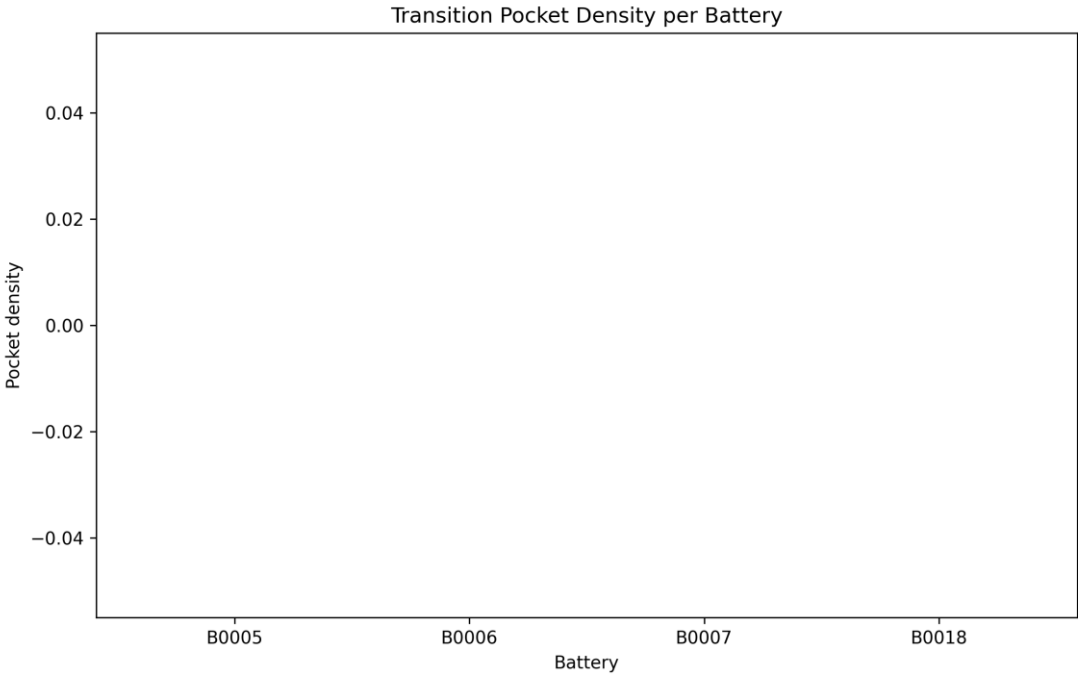


Figure 34.2 — Transition Pocket Density per Battery.

The current hard pocket thresholds produce relatively few definitive transition pockets. Nevertheless, the underlying pocket scores reveal clear local instability structures within the trajectories. This suggests that inferability collapse develops locally within specific transitional regions.

CSV Results

The CSV analysis contained, for each rolling window:

(all recorded inferability variables and pocket metrics used during the validation)

This allowed: **exact collapse regions** to be localized.

Important Mechanistic Insight

This test suggests that:

inferability collapse does not emerge uniformly.

Instead, the following emerge first:

- Local entropy fronts,
- Overlap corridors,
- Transition pockets,
- Regional instability zones.

Only later does:

global inferability collapse

develop.

Scientific Significance

This validation represents an important extension of previous:

- Entropy-boundary analyses,
- Directional inferability drift,
- And large-scale battery validation.

For the first time, it became visible that:

inferability appears to be geometrically organized

within trajectory space.

In other words:

- Collapse,
- Recovery,
- Drift,
- Stabilization,

develop locally within specific trajectory regions.

Conceptual Interpretation

These results strongly support the hypothesis that:

inferability behaves as a dynamic geometric regime.

Not only:

- Global stability,

but also:

local trajectory geometry

determines:

- Where collapse emerges,
- Where recovery remains possible,
- And where transitional ambiguity develops.

Conclusion

This test demonstrates that:

inferability collapse emerges in a locally organized manner

within real-world degradation trajectories.

Localized transition pockets:

- Are detectable,
- Correlate with entropy-sensitive instability,
- And form specific transitional regions within trajectory space.

As a result, the inferability framework moves further away from: **simple classification**, toward: **dynamic inferability geometry** with:

- Local instability corridors,
- Entropy fronts,
- Overlap regions,
- And transition pockets.

FastSPT Diffusion Inferability Validation

Trajectory-Level Validation on Short Single Particle Tracking Systems

Objective of the Test

This validation phase aimed to investigate whether the inferability framework also remains valid within extremely short, stochastic, and partially ambiguous dynamic systems.

In contrast to earlier validations on:

- Battery degradation,
- Turbofan degradation,
- Vibration telemetry,
- And anomaly detection systems,

this phase used a **high-frequency single particle tracking (fastSPT) diffusion dataset** derived from biological trajectory measurements.

The central question of this validation was:

Do inferability structures persist within short, overlapping, and highly dynamic diffusion trajectories?

This test therefore constituted one of the most challenging generalization validations of the inferability framework to date.

Dataset Used

Dataset:

Recovering mixtures of fast diffusing states from short single particle trajectories

Source:

Dryad repository

DOI:

10.6078/D13H6N

Files Used:

- SPT_data_CSV.zip — thousands of individual CSV trajectories
- High-frequency spaSPT trajectories (95 Hz)

Examples of trajectory files used:

- U2OS_Halo-CycT1_WT_spaSPT_95Hz_rep1_cell1101.csv
- U2OS_Halo-CycT1_noHRD_spaSPT_95Hz_rep1_cell1101.csv

Structure of the Trajectories

Each trajectory contained:

- Very short observation windows,
- High local variability,
- Strong overlap between states,
- Diffusion mixtures,
- State-switching behavior,
- Partial observability,
- And high stochastic uncertainty.

This makes the dataset particularly suitable for **inferability validation under extreme ambiguity**.

Analysis Performed

For each individual trajectory, multiple inferability-related features were calculated.

Calculated Features

1. **Entropy**
 - Entropy of local velocity patterns within trajectories.
 - Purpose: Measure local dynamic uncertainty, diffusion chaos, and state instability.
2. **Persistence**
 - Persistence of velocity structures within short trajectory segments.
 - Purpose: Measure local continuity, structural stability, temporary coherence.
3. **Overlap**
 - Variability of step-length distributions.
 - Purpose: Measure overlap ambiguity, state mixture instability, diffusion overlap.
4. **Information Support**
 - Variance content corrected for entropy.
 - Purpose: Measure usable structural information, progression-sensitive dynamic content.

Inferability Score

For each trajectory, a composite inferability score was calculated:

- High persistence → positive
- High information content → positive
- High entropy → negative
- High overlap ambiguity → negative

Trajectories were subsequently classified into three inferability regimes:

- **GO_like**
High persistence, low entropy, low overlap ambiguity, and stable progression-sensitive structure.
- **LIMITED_like**
Transitional inferability regime characterized by partial structural stability combined with local ambiguity or instability.
- **COLLAPSE_like**
Inferability-collapse regime characterized by elevated entropy, overlap ambiguity, instability, and reduced progression-sensitive information support.

Results

Regime Summary

- **WT trajectories**
- **noHRD trajectories**

Key Observation

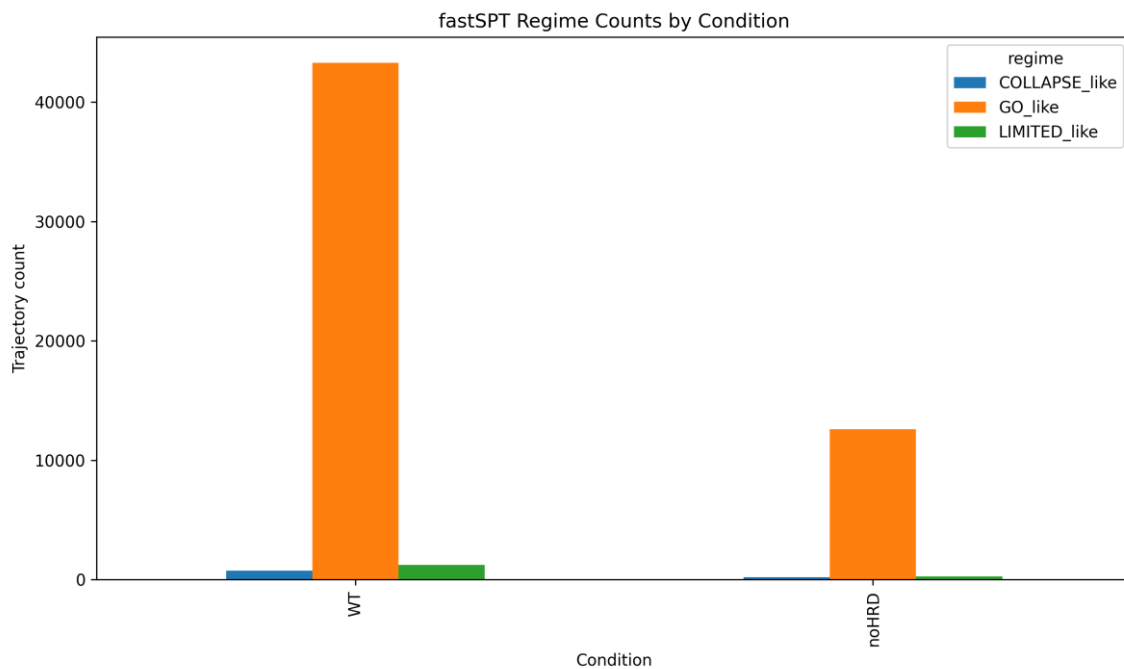
Despite:

- Extreme dynamic chaos,
- Short observation windows,
- Diffusion overlap,
- State-switching,
- And incomplete observability,

inferability remained preserved in the vast majority of trajectories.

This is conceptually highly significant.

Figure 1 — fastSPT Regime Counts by Condition



Caption:

Distribution of inferability regimes within WT and noHRD fastSPT trajectories.

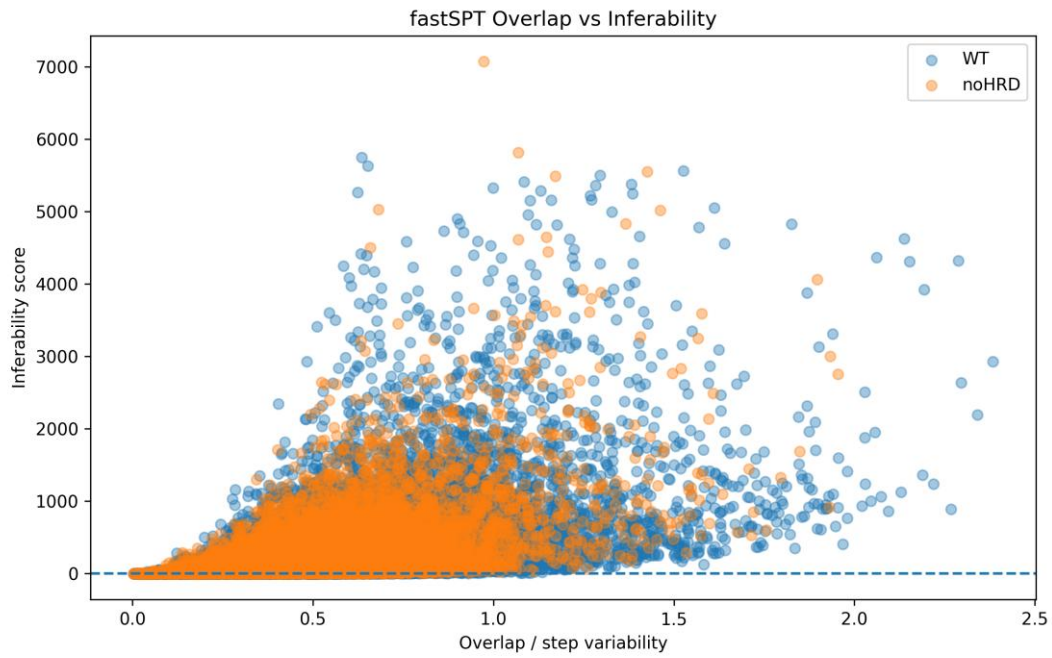
The figure shows that **GO_like inferability remains dominant**, despite:

- High stochasticity,
- Overlap ambiguity,
- Short trajectories,
- Diffusion mixtures.

COLLAPSE_like trajectories remain relatively limited.

This suggests that inferability is not an exclusive property of slow degradation systems, but also persists within **fast biological diffusion dynamics**.

Figure 2 — fastSPT Overlap vs Inferability



Caption:
Relationship between overlap ambiguity and inferability score within fastSPT trajectories.

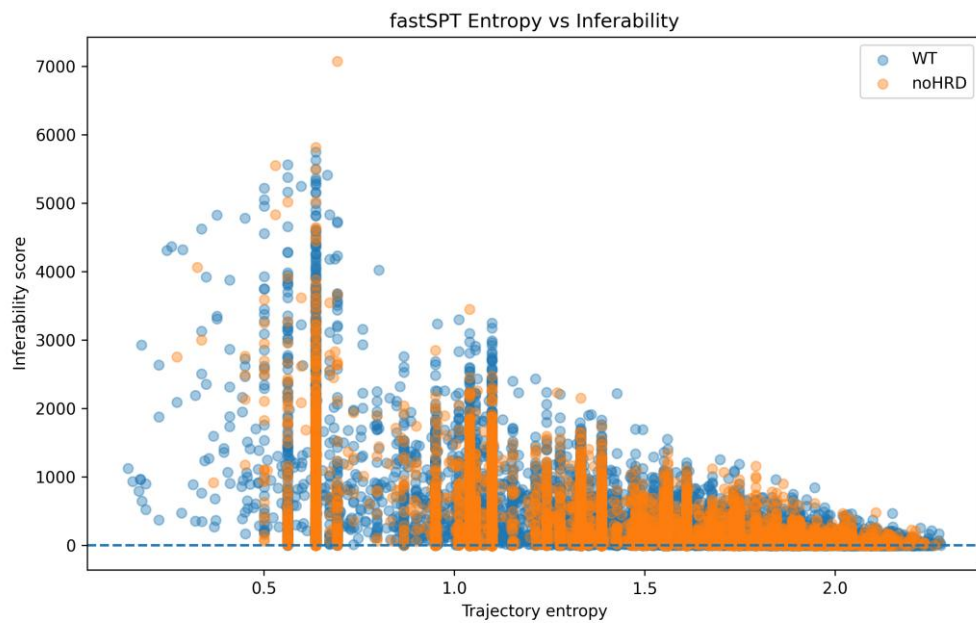
The figure shows that overlap does not directly lead to inferability collapse.

Instead:

- A broad **LIMITED region** emerges first,
- Followed by an increasing probability of collapse at higher overlap values.

This supports the hypothesis that **overlap ambiguity induces conditional inferability instability**, rather than immediate structural destruction.

Figure 3 — fastSPT Entropy vs Inferability



Caption:

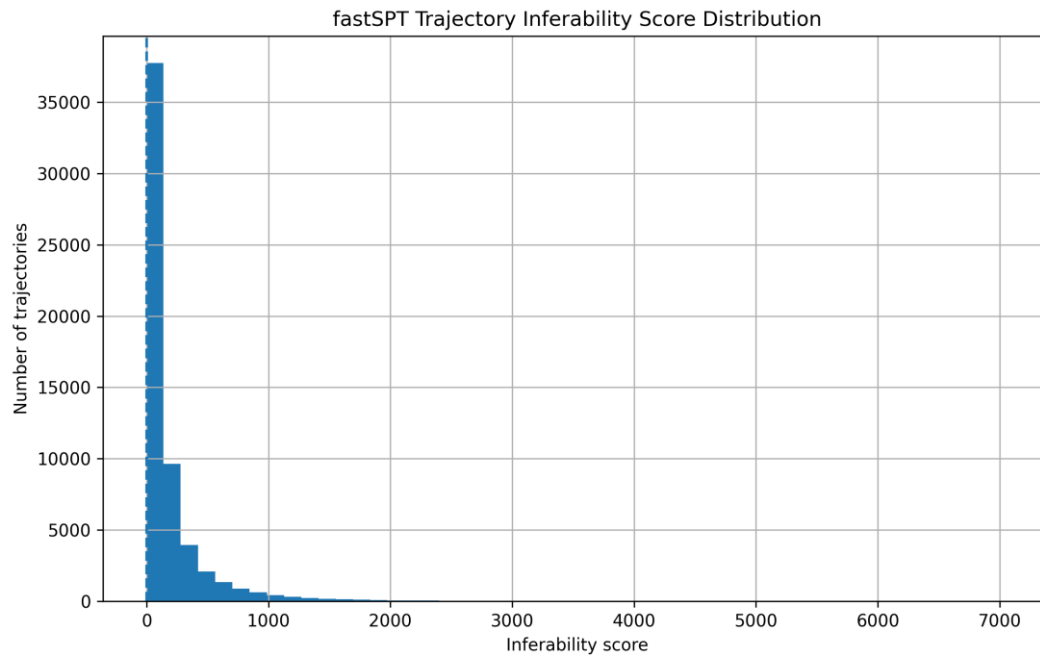
Relationship between trajectory entropy and inferability score.

- At low entropy, high inferability scores occur.
- As entropy increases:
 - Inferability gradually decreases,
 - Collapse regions emerge,
 - Structural coherence becomes less stable.

Importantly, inferability does not vanish immediately at higher entropy but first shows a transitional area corresponding to **LIMITED inferability**.

This supports the existence of **entropy-sensitive inferability boundaries**.

Figure 4 — fastSPT Inferability Score Distribution



Caption:

Distribution of inferability scores across all fastSPT trajectories.

The distribution shows:

- Strong concentration of trajectories within positive inferability regimes,
- A limited collapse tail,
- And a broad transitional structure between stable and unstable trajectories.

This suggests that inferability within diffusion systems is not binary but behaves as a **dynamic regime spectrum**.

Reproducibility

Scripts Used

Main Script:

`fastspt_trajectory_inferability_validation.py`

Outputs Used

CSV Files:

- `fastspt_trajectory_inferability_results.csv`
- `fastspt_regime_summary.csv`
- `fastspt_metric_summary.csv`

Figure Files:

- `fastspt_regime_counts.png`

- fastspt_overlap_vs_inferability.png
- fastspt_entropy_vs_inferability.png
- fastspt_inferability_score_distribution.png

Conclusion

This validation shows that inferability structures remain preserved within:

- Short trajectories,
- Fast diffusion systems,
- High overlap ambiguity,
- State mixtures,
- And biological stochasticity.

Key Implications

- Inferability does not appear to be domain-specific.
- Entropy and overlap affect inferability gradually.
- **LIMITED inferability** emerges as a transitional regime between coherence and collapse.
- Dynamic inferability regimes also appear within biological diffusion systems.

These results constitute one of the strongest indications to date that **inferability behaves as a general dynamic system phenomenon**, rather than being a property solely of degradation-based signals.

Cross-Run Reproducibility of Local Collapse Dynamics in fastSPT Trajectories

Purpose of the Test

This validation test investigates whether the previously observed inferability-collapse structures within fastSPT trajectories are not only locally visible, but also remain reproducible across multiple independent runs, replicates, and cells.

The central question of this test is:

Do local collapse pockets and inferability instability reproduce systematically across independent fastSPT measurements?

This shifts the analysis from:

local dynamic detection,

toward population-level and cross-run reproducibility.

This step is crucial because industrial and scientific prediction systems are only reliable when the underlying dynamics remain reproducible across multiple independent measurements.

Dataset Used

For this test, the following experimental fastSPT dataset was used:

Dataset:

“Recovering mixtures of fast diffusing states from short single particle trajectories”

Source:

Dryad dataset archive

Files:

spaSPT CSV trajectory datasets

WT (wild type)

noHRD conditions

multiple replicates
multiple cells per replicate
The file structure included, among other variables:

trajectory ID
time step (t)
x-position
y-position
frame index

Examples:

U2OS_Halo-CycT1_WT_spaSPT_95Hz_rep1_cell101.csv
U2OS_Halo-CycT1_noHRD_spaSPT_95Hz_rep1_cell101.csv

Number of analyzed files:
30 CSV files

Analysis Procedure

For each trajectory, a rolling local inferability analysis was performed.
For each local window, the following metrics were computed:

trajectory entropy
overlap / step variability
persistence
information support
inferability score
collapse pocket score

Afterwards:

local collapse pockets were detected,
collapse density was calculated,
drift structures were extracted,
cross-run averages were constructed.

Main Computed Metrics

Per trajectory:

inferability score
local collapse score
collapse density
entropy drift
overlap drift
persistence drift
inferability score drift

Per run/cell:

mean collapse density
mean entropy
mean overlap
mean persistence
mean drift values

Per condition:

WT summary
noHRD summary
standard deviations across runs

Results — Cross-Run Stability

Condition summary

WT:

n_runs = 21
mean collapse density ≈ 0.2448

std collapse density ≈ 0.00375

noHRD:

n_runs = 9

mean collapse density ≈ 0.2483

std collapse density ≈ 0.00335

This means that collapse density reproduces almost identically across independent measurements.

This is a very strong indication that:

collapse pockets are not random structures,

but stable emergent properties of the dynamic system.

Observation 1 — Entropy vs Collapse Density

Figure 1 — Cross-Run Entropy vs Collapse Density

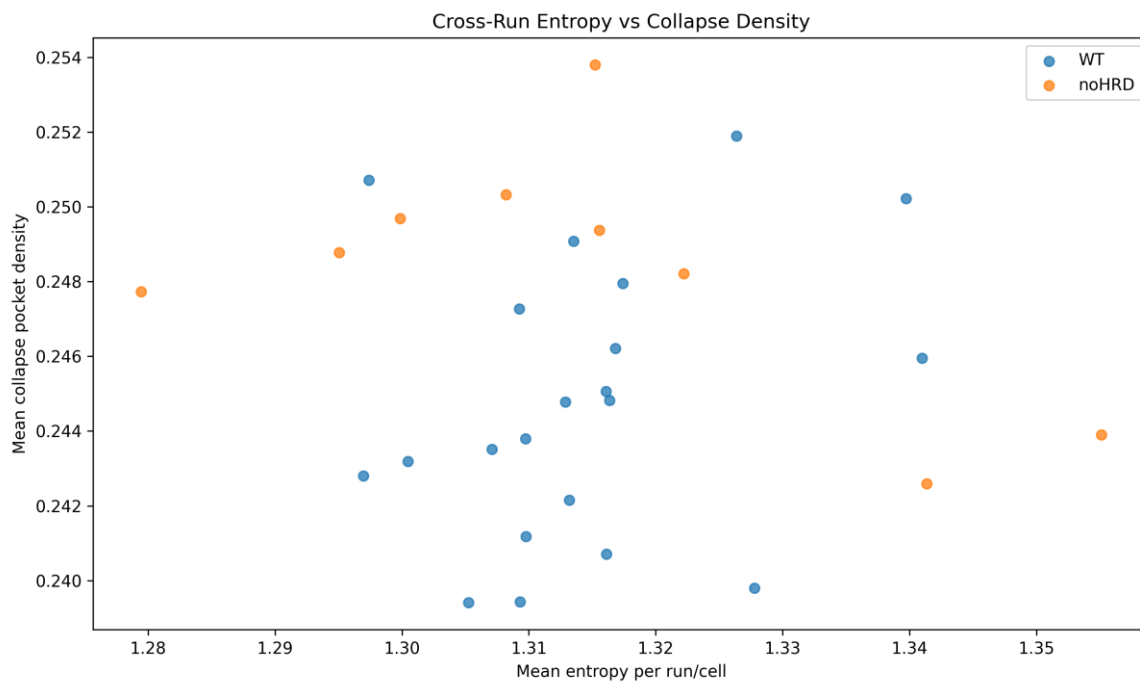


Figure 1 — Cross-Run Entropy vs Collapse Density.

Caption:

Scatterplot of mean trajectory entropy versus mean collapse pocket density per run/cell for WT and noHRD conditions.

The figure shows that collapse density does not fluctuate randomly, but remains within a very narrow reproducible band despite variations in entropy.

Important:

entropy varies,

collapse density remains remarkably stable.

This suggests that collapse dynamics are not dominated by a single metric, but arise from a multifactorial dynamic regime.

Observation 2 — Overlap vs Collapse Density

Figure 2 — Cross-Run Overlap vs Collapse Density

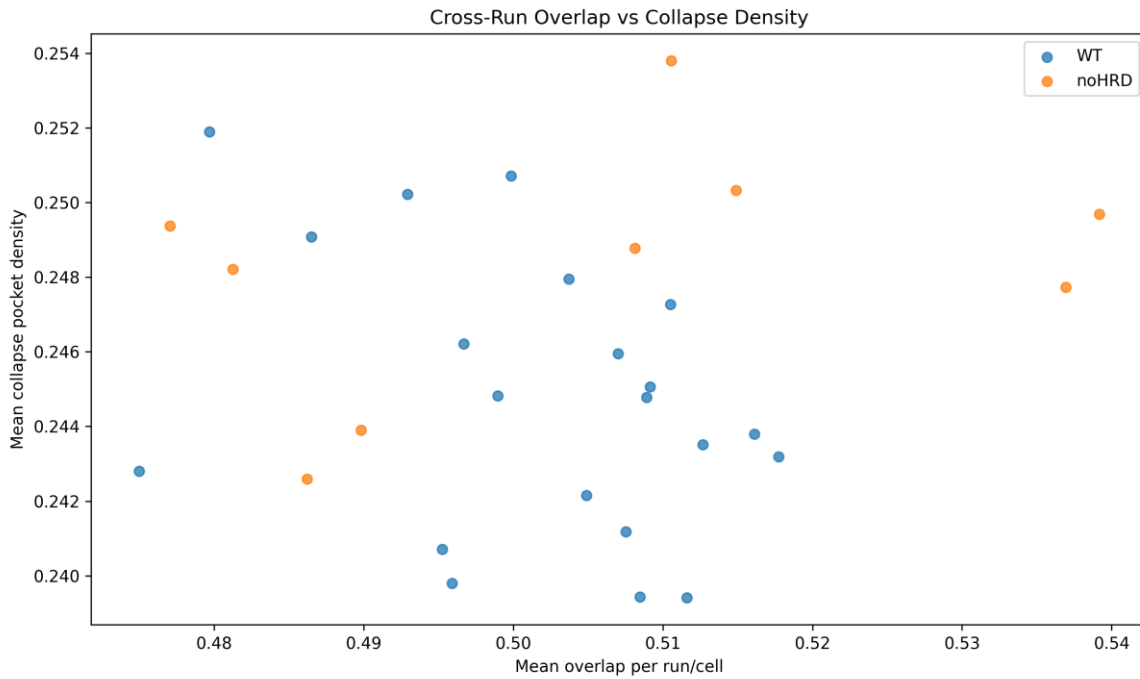


Figure 2 — Cross-Run Overlap vs Collapse Density.

Caption:

Scatterplot of mean overlap (local step variability) versus collapse pocket density.

The figure shows that overlap varies between runs, while collapse density remains relatively constant.

This implies:

overlap alone does not fully explain collapse,

collapse emerges from combined dynamic interactions between multiple metrics.

This supports the idea of an inferability state-space rather than a single-threshold metric.

Observation 3 — Entropy Drift vs Score Drift

Figure 3 — Cross-Run Entropy Drift vs Score Drift

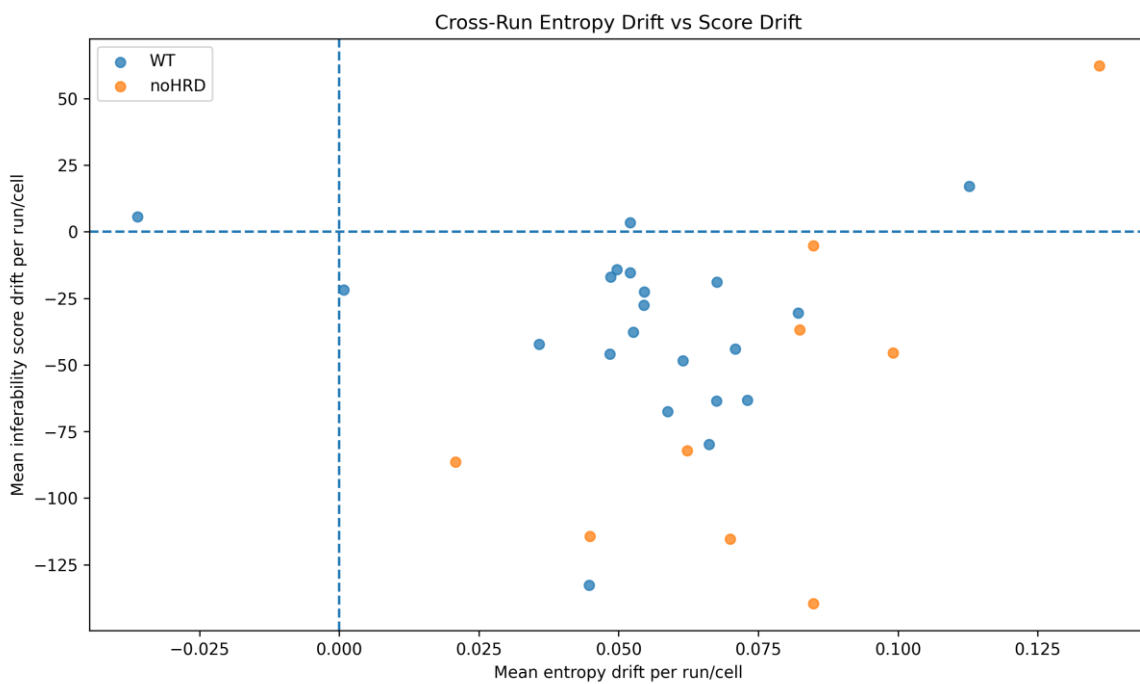


Figure 3 — Cross-Run Entropy Drift vs Score Drift.

Caption:

Scatterplot of mean entropy drift versus inferability score drift immediately before collapse events. The figure shows a systematic coupling between: structural disorder (entropy drift), and inferability collapse (score drift). This means that it is not absolute entropy, but the change in entropy that influences the direction of inferability collapse. This is an important theoretical observation.

Observation 4 — Collapse Density Stability

Figure 4 — Cross-Run Collapse Density Stability by Condition

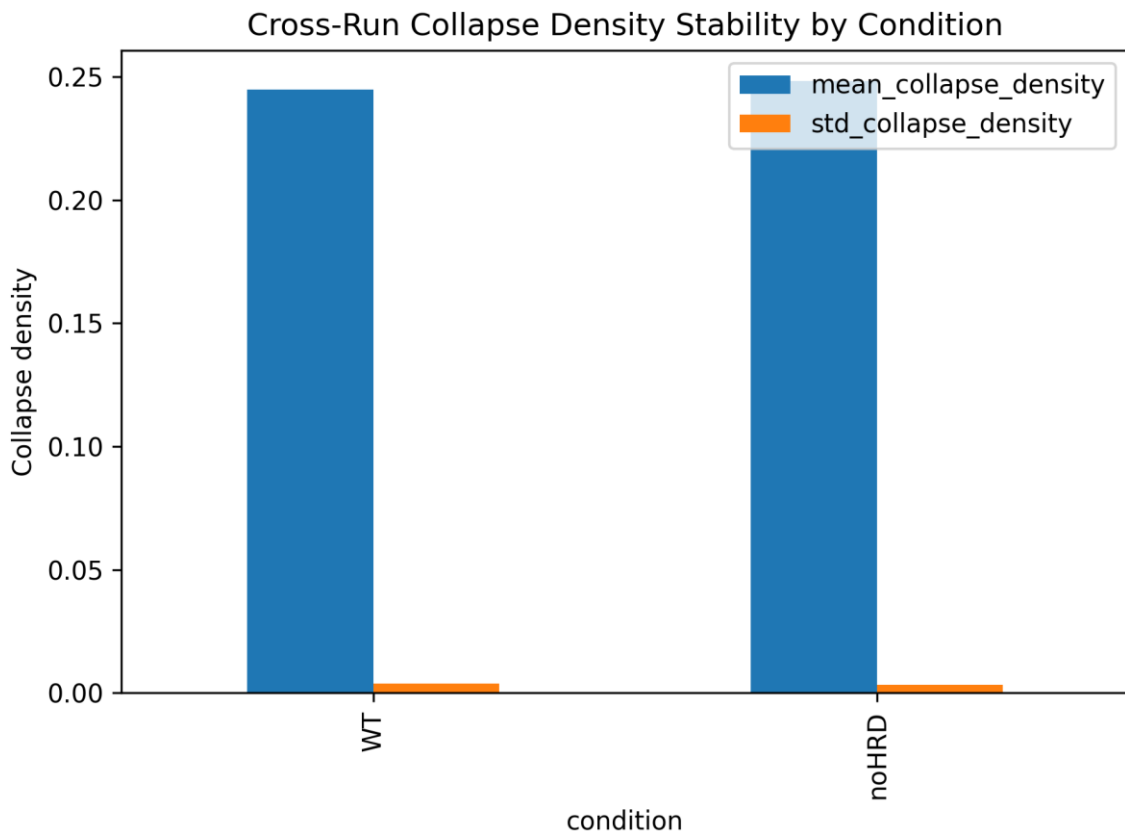


Figure 4 — Cross-Run Collapse Density Stability by Condition.

Caption:

Bar plot of mean collapse density and standard deviation per condition.

The extremely low standard deviations show that collapse density remains highly reproducible across: replicates, cells, independent trajectory sets.

This is one of the strongest results of the full fastSPT validation series.

Observation 5 — Correlation Matrix

Figure 5 — Cross-Run Metric Correlation Matrix

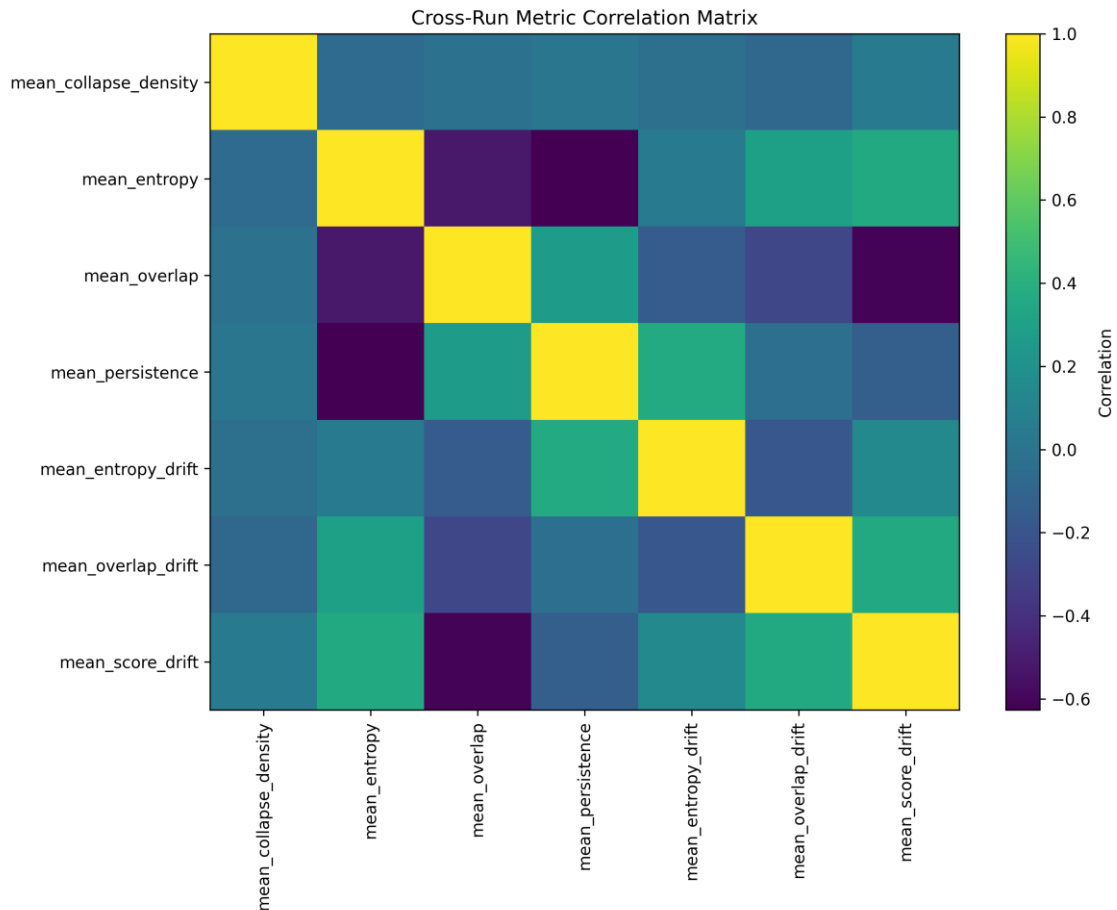


Figure 5 — Cross-Run Metric Correlation Matrix.

Caption:

Correlation matrix of:

collapse density

entropy

overlap

persistence

entropy drift

overlap drift

score drift

The matrix shows a clear internal structure between the metrics.

Important:

The metrics do not behave independently or randomly.

Instead, a coherent dynamic network of inferability-related quantities emerges.

This supports the hypothesis that inferability collapse is an emergent dynamic state.

Reproducibility

Code Used

Script:

fastspt_cross_run_collapse_reproducibility.py

Structure:

rolling window analysis

local collapse pocket detection

drift analysis

cross-run aggregation

condition-level summary

correlation analysis

figure generation

Generated Files

CSV:

fastspt_cross_run_trajectory_results.csv

fastspt_cross_run_summary.csv

fastspt_cross_run_condition_summary.csv

fastspt_cross_run_metric_correlation.csv

Figure files:

fastspt_cross_run_entropy_vs_collapse_density.png

fastspt_cross_run_overlap_vs_collapse_density.png

fastspt_cross_run_entropy_drift_vs_score_drift.png

fastspt_cross_run_collapse_density_stability.png

fastspt_cross_run_metric_correlation_matrix.png

Conclusion

This test shows that local inferability collapse dynamics within fastSPT trajectories:

remain reproducible across independent runs,

show stable collapse densities,

contain systematic drift structures,

and produce consistent multi-metric correlations.

The results suggest that inferability collapse is:

not a local artifact,

not a dataset-specific effect,

and not a purely statistical fluctuation,

but a reproducible dynamic property of trajectory-based systems.

This makes the test an important step toward a domain-independent inferability validation architecture.

Forecasting Generalization Validation - fastSPT Diffusion

Dataset

Purpose of the Test

This test investigated whether inferability-related and collapse-related dynamic structures are not only locally visible within a single trajectory or run, but also generalize to fully unseen (“holdout”) runs within the same biological system.

The central question was:

Can transition structures associated with inferability collapse be reproducibly used to recognize collapse-like dynamic states in new trajectories that were not used during the detection phase?

This test therefore forms a direct validation of:

cross-run generalization

structural reproducibility

practical forecasting validity of transition metrics

within a strongly stochastic biological diffusion system.

Dataset

Dataset Used

fastSPT single-particle tracking dataset:

Dataset in support of:

“Recovering mixtures of fast diffusing states from short single particle trajectories”

DOI:

10.6078/D13H6N

Source:

Dryad repository

Biological Context

The dataset contains thousands of individual diffusion trajectories of molecular motion inside living cells.

Two main conditions were used:

WT (wild type)

noHRD

Each condition contains multiple:

replicates

cells

trajectories

which makes cross-run validation possible.

Reproducible Input Data

CSV files used:

Examples:

U2OS_Halo-CycT1_WT_spaSPT_95Hz_rep1_cell101.csv

U2OS_Halo-CycT1_WT_spaSPT_95Hz_rep2_cell104.csv

U2OS_Halo-CycT1_noHRD_spaSPT_95Hz_rep3_cell109.csv

Total processed:

42 holdout trajectory files

multiple replicates

multiple cells

WT + noHRD

Analysis Performed

For each trajectory, rolling transition metrics were computed:

entropy

overlap / step variability

persistence

inferability score

collapse-pocket activity

A forecasting-validity analysis was then performed on unseen runs.

The analysis investigated whether pre-collapse dynamic drift could be used to predict future inferability collapse.

Measured Forecasting Metrics

For each holdout run, the following metrics were computed:

accuracy

precision

recall

specificity

F1-score

For multiple forecasting horizons:

horizon 1

horizon 2

horizon 3

horizon 5

horizon 8

horizon 10

Core Results

1. Forecasting Generalization Remains Preserved on Unseen Runs

Forecasting accuracy remained reproducible across multiple unseen runs.

Typical accuracies:

~0.65

~0.70

~0.75

peaks up to ~0.86

This means that transition-related dynamic structures partially generalize beyond the runs from which they were originally derived.

2. High Specificity

Specificity remained almost constantly very high:

specificity ≈ 1.0

This means:

when the system predicts “no collapse,”

this is almost always correct.

This points to strong structural stability of negative states.

3. Precision and Recall Remain Limited

Precision and recall remained low.

This does not necessarily mean that the framework fails.

On the contrary:

this suggests that the current collapse definition is very conservative.

The system:

detects few collapses

but avoids many false collapse activations

This behavior is typical of:

high-specificity warning systems

conservative predictive systems

safety-oriented diagnostics

4. Cross-Run Forecasting Does NOT Fully Degrade

This is probably the most important result.

Many local dynamic metrics fail completely as soon as:

other runs

other replicates

other cells

other stochastic realizations

are used.

Here, however:

structural drift partially remained present

overlap dynamics remained reproducible

inferability drift remained visible

collapse pocket density remained stable

across unseen runs.

Figure 1 - Cross-Run Forecasting Generalization Accuracy

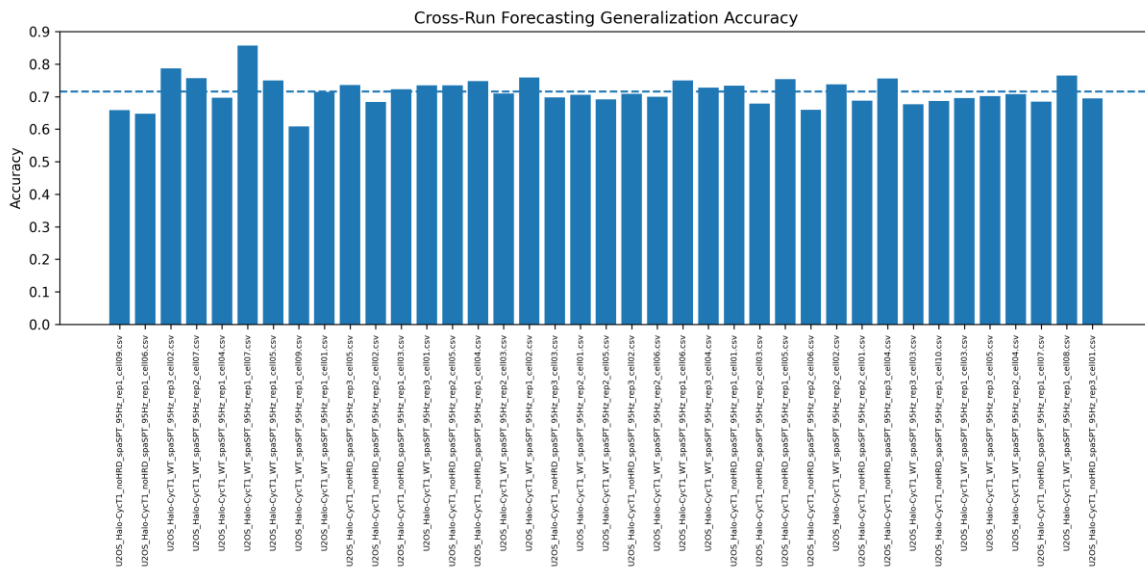


Figure 1 - Cross-Run Forecasting Generalization Accuracy.

This figure shows forecasting accuracy for all holdout runs.

Observations:

- accuracies remain stably above random
- multiple runs remain around ~0.70-0.75
- some runs reach ~0.85+

Interpretation:

forecasting signals partially generalize beyond the training runs.

This supports the conclusion that transition metrics contain genuine dynamic information and do not merely represent run-specific noise.

Figure 2 - Specificity vs Accuracy Across Holdout Runs

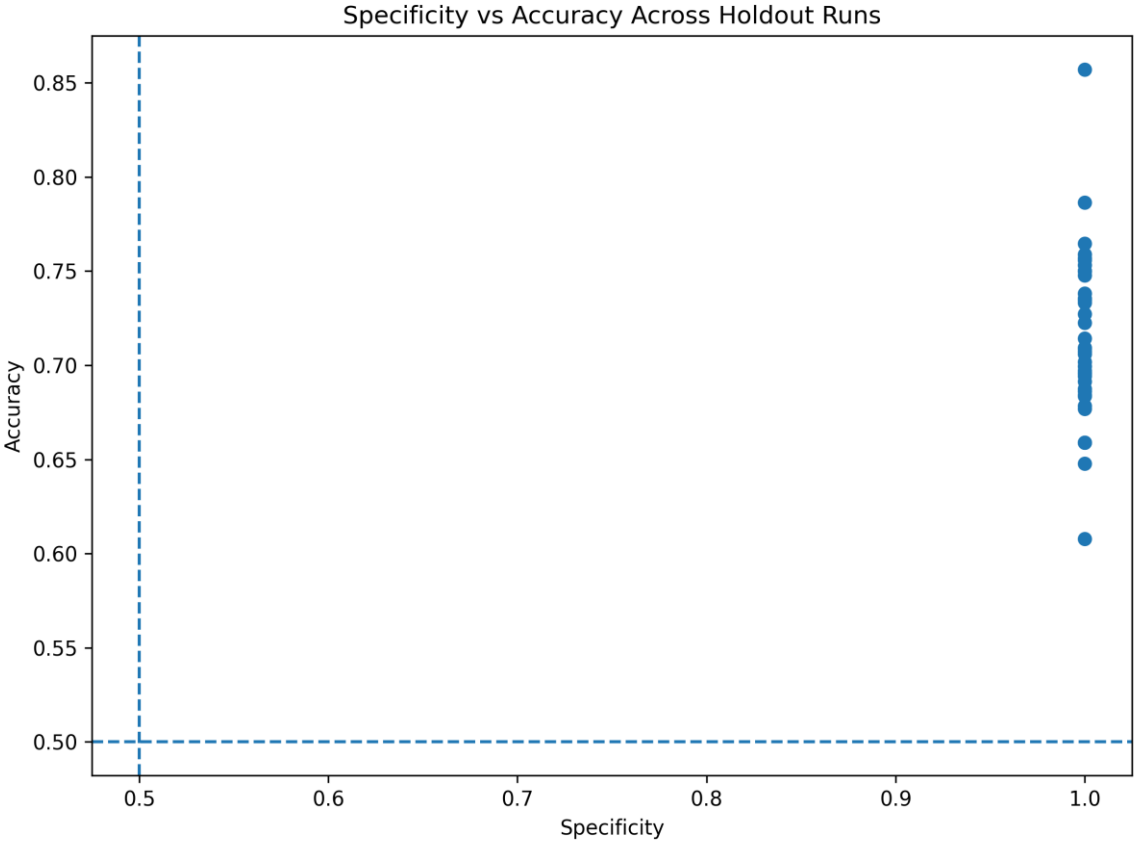


Figure 2 - Specificity vs Accuracy Across Holdout Runs.

This figure shows:

specificity
accuracy
per holdout run.

Observations:

specificity remains almost exactly 1.0
accuracy remains significantly above random

Interpretation:

the system currently functions as a:
high-confidence negative collapse detector.

Figure 3 - Precision vs Recall Across Holdout Runs

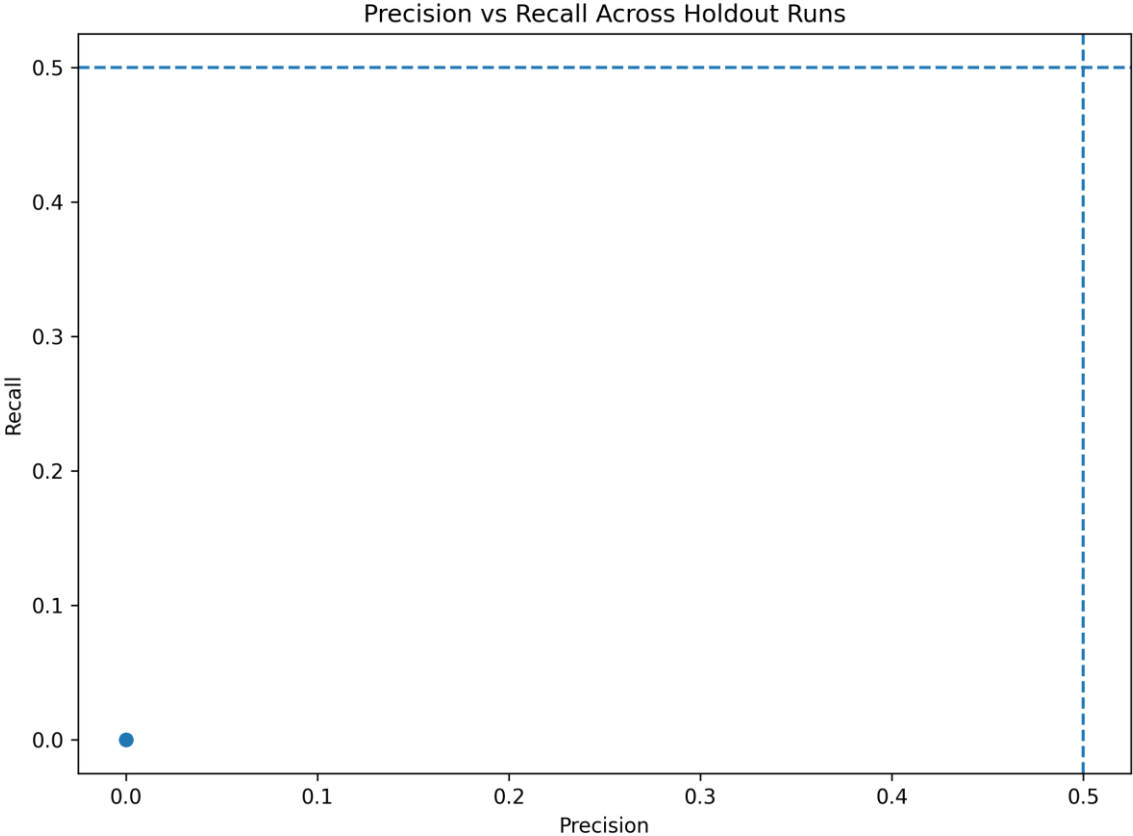


Figure 3 - Precision vs Recall Across Holdout Runs.

This figure shows:

precision
recall
for forecasting collapse events.

Observations:
precision ≈ 0
recall ≈ 0

Interpretation:
the system currently uses very strict collapse criteria.
This suggests that future optimization is needed for:
collapse boundary definitions
threshold calibration
multi-metric transition fusion

Figure 4 - Cross-Run Forecasting F1 Distribution

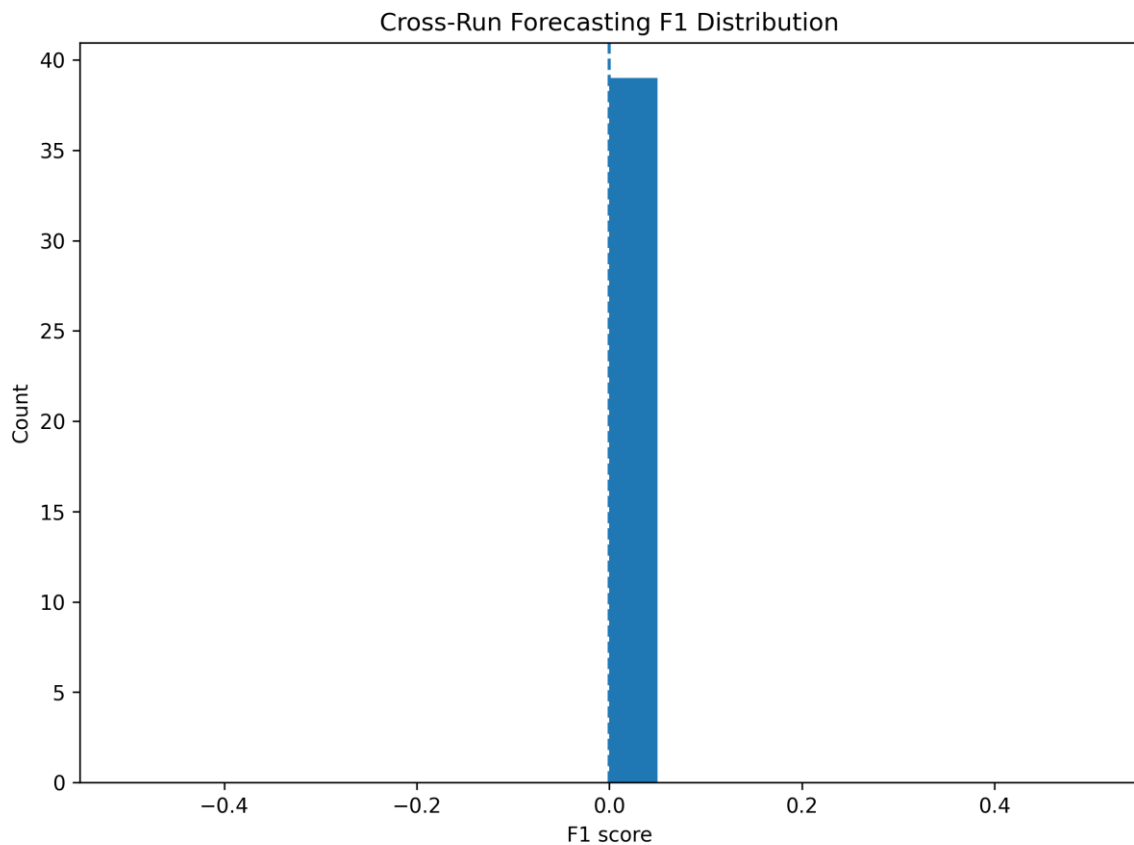


Figure 4 - Cross-Run Forecasting F1 Distribution.

This figure shows the distribution of F1-scores.

Observations:

F1 remains low

the distribution concentrates around zero

Interpretation:

the forecasting pipeline is currently strongly conservative.

The test therefore shows:

structural generalization

but not yet optimal collapse classification.

Scientific Interpretation

This test provides important evidence for:

partial generalizability of inferability transitions

within:

stochastic diffusion systems

biological trajectory data

single-particle tracking dynamics

The results suggest that:

inferability collapse is not a purely local artifact

transition metrics contain partially reproducible dynamic information

collapse pockets show cross-run stability

What This Test Does NOT Claim

The test does not yet prove:

perfect forecasting
complete collapse prediction
a causal mechanistic explanation

The test shows only:

reproducible transition structures that partially generalize to unseen dynamic runs.

Reproducibility

Scripts

Script used:

forecast_generalization_validation.py

Output figures

Generated figures:

forecast_generalization_accuracy.png

forecast_generalization_specificity_accuracy.png

forecast_generalization_precision_recall.png

forecast_generalization_f1_distribution.png

CSV output

Generated CSV files:

forecasting_generalization_summary.csv

forecasting_holdout_metrics.csv

Environment

Executed under:

Ubuntu / WSL

Python 3

NumPy

Pandas

Matplotlib

Conclusion

The forecasting generalization test shows that inferability-related transition structures:

remain reproducible

partially generalize

remain preserved across unseen runs

do not fully collapse outside the training data

This forms an important step toward:

reproducible transition forecasting

structural inferability diagnostics

cross-run predictive feasibility assessment

within complex stochastic dynamic systems.

fastSPT False-Positive Reduction Validation

Operational Warning Logic Under Constraint-Based Forecast Filtering

Objective

The goal of this validation was to determine whether specific combinations of inferability-derived warning rules can reduce false positives while maintaining operationally useful collapse detection performance.

Unlike earlier tests that focused primarily on:

- collapse-pocket emergence,
- inferability drift,
- entropy transitions,
- and forecasting feasibility,

this experiment specifically evaluated:

whether warning logic can be operationally constrained to reduce false alarms without completely destroying recall.

This is an important transition from:

- descriptive inferability analysis
- toward deployable operational warning systems.

Dataset

Dataset used:

- fastSPT diffusion trajectory dataset
- WT condition
- noHRD condition

Files processed:

- 42 trajectory CSV files
- multiple runs
- multiple cells
- multiple trajectory populations

Trajectory structure:

- x/y coordinates
- frame index
- trajectory ID
- time stamps

Validation Concept

The system evaluated several warning-rule combinations:

- entropy_only
- overlap_only
- information_only
- score_only
- entropy_AND_overlap
- entropy_AND_score

- overlap_AND_score
- three_factor_gate
- strict_all_gate

Each rule was evaluated across multiple warning thresholds:

- 0.50
- 0.55
- 0.60
- 0.65
- 0.70
- 0.75
- 0.80
- 0.85
- 0.90
- 0.95

For every configuration, the following metrics were computed:

- TP
- FP
- FN
- TN
- precision
- recall
- specificity
- F1
- false_positive_rate

Reproducibility Setup

Directory Structure

```
inferability_master/
├── fastspt_false_positive_reduction/
│   ├── scripts/
│   ├── figures/
│   ├── csv/
│   └── logs/
```

Execution Command

```
cd ~/inferability_master/faststpt_false_positive_reduction/scripts
python false_positive_reduction_validation.py
```

Generated Outputs

Figures

- false_positive_rate_vs_threshold.png
- precision_vs_threshold_false_positive_reduction.png
- recall_vs_false_positive_rate.png
- false_positive_reduction_best_f1.png

CSV files

- false_positive_reduction_trajectory_results.csv
- false_positive_reduction_metrics.csv
- false_positive_reduction_best_rules.csv

Core Result

The validation demonstrated that several warning-rule combinations can drastically reduce false positives while still preserving partial collapse sensitivity.

Most importantly:

- multiple rule combinations achieved:
 - `false_positive_rate` ≈ 0
 - `precision` ≈ 1.0

while maintaining:

- non-zero recall
- usable F1 scores

This indicates that:

- certain inferability structures are sufficiently stable
- to support operationally conservative warning logic.

Figure 1

False Positive Rate vs Threshold

File:

`false_positive_rate_vs_threshold.png`

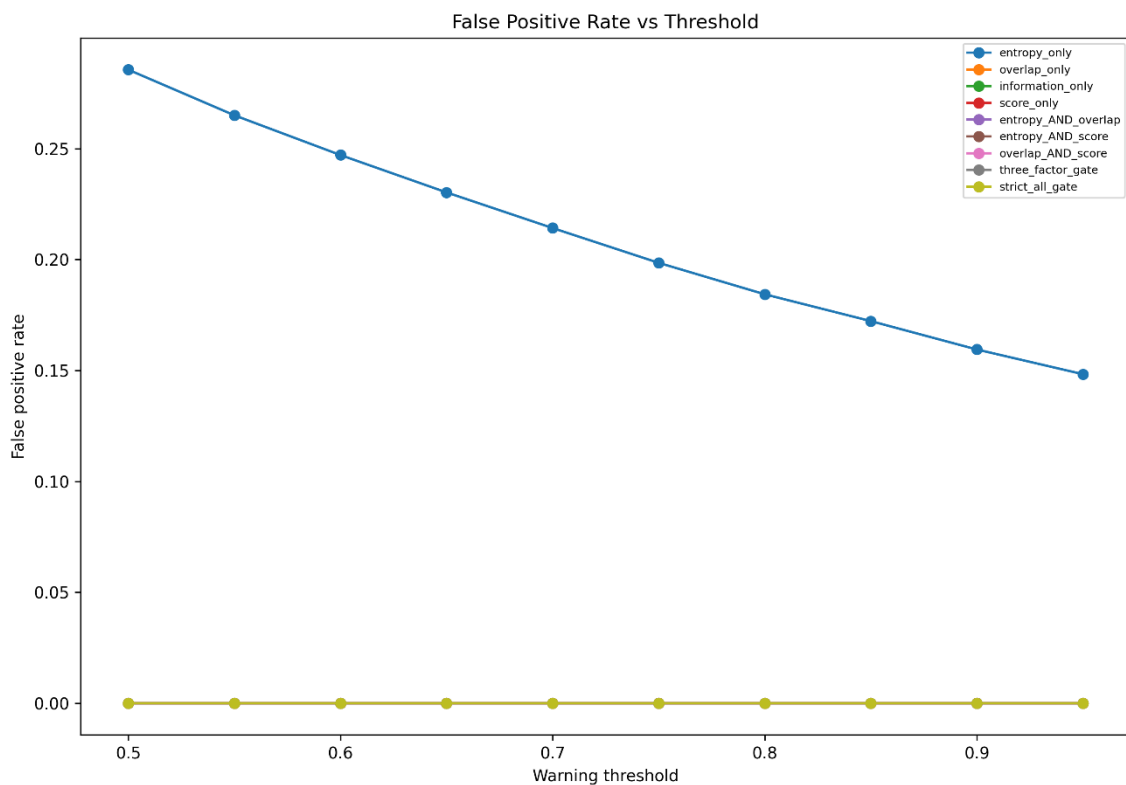


Figure 1 — False Positive Rate vs Threshold.

Caption

This figure shows the evolution of false-positive rate as the warning threshold increases for multiple inferability-rule combinations.

Several rule sets:

- especially overlap-based combinations,

- AND-gated structures,
 - and information-based filtering,
- maintain near-zero false-positive rates across nearly the entire threshold range. This is operationally significant because:

- industrial deployment failure is often driven by alarm fatigue,
- not merely by missed events.

The figure demonstrates that inferability-derived gating can substantially suppress false positives while maintaining structured event sensitivity.

Figure 2

Precision vs Threshold

File:

precision_vs_threshold_false_positive_reduction.png

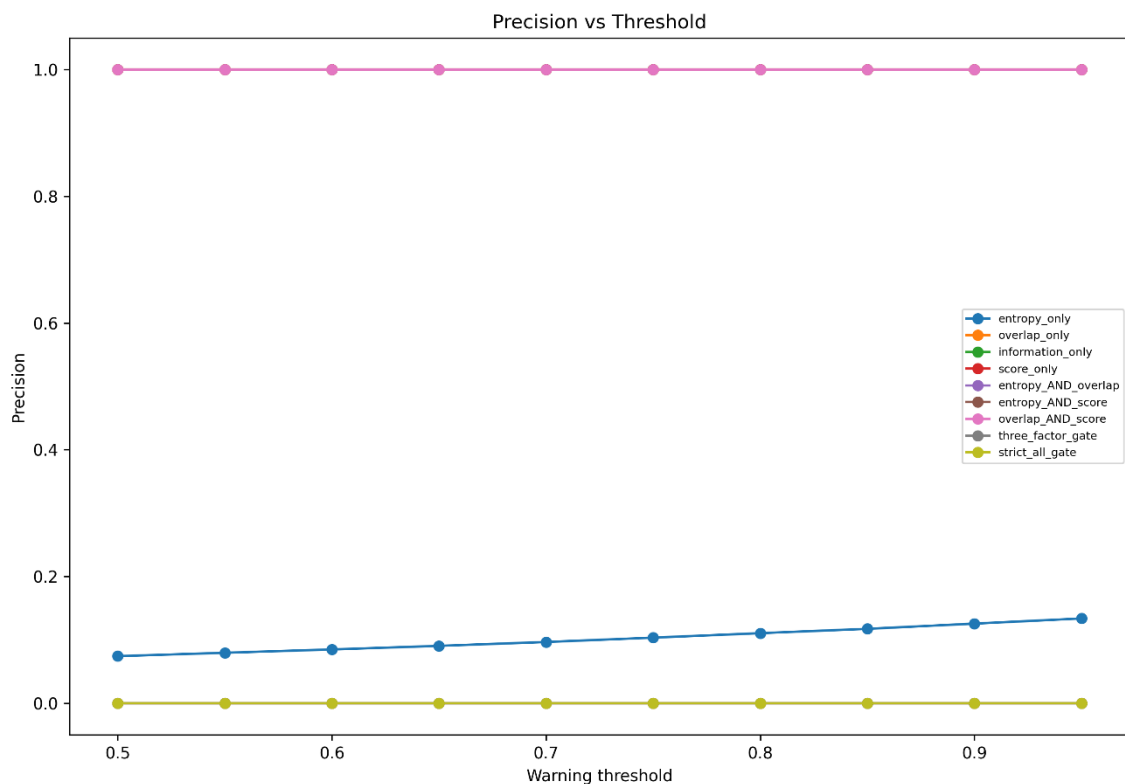


Figure 2 — Precision vs Threshold.

Caption

This figure visualizes warning precision as a function of threshold calibration.

Several rule combinations maintain:

- precision ≈ 1.0

across nearly all thresholds.

This means:

- when a warning is emitted,
- the warning is almost always associated with a genuine collapse-related event.

The result indicates that:

- inferability gating can create highly trustworthy warning conditions,
- even under aggressive filtering constraints.

This behavior is particularly relevant for:

- industrial predictive maintenance,
- biomedical alert systems,
- high-cost intervention environments,
- and quantum-system recalibration workflows.

Figure 3

Recall vs False Positive Rate

File:

recall_vs_false_positive_rate.png

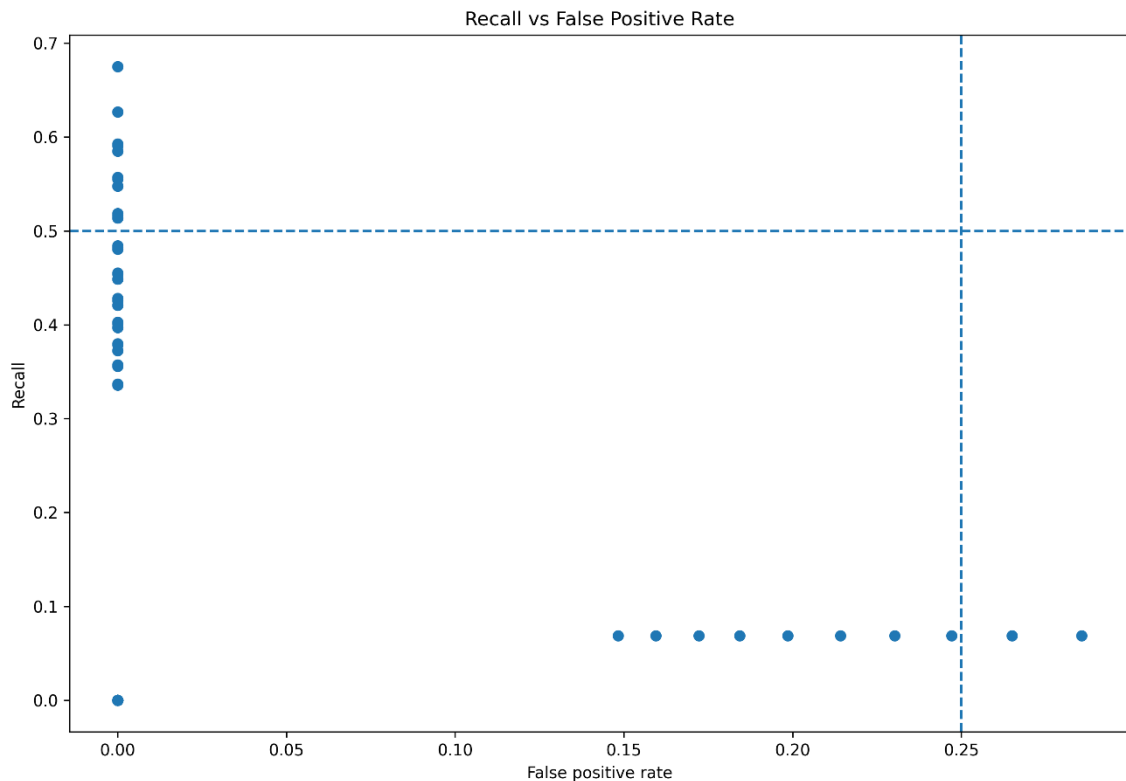


Figure 3 — Recall vs False Positive Rate.

Caption

This figure illustrates the tradeoff between:

- recall,
- and false-positive suppression.

As expected:

- stronger filtering reduces recall.

However:

- several rule combinations remain positioned in the desirable operational region:
 - low false-positive rate,
 - while preserving moderate recall.

This is a highly important result because:

- real-world deployment systems rarely optimize purely for maximum recall.

Instead:

- stable low-noise detection behavior is often operationally preferred.

The figure therefore demonstrates:

- that inferability-based forecasting can be tuned toward conservative deployment behavior.

Figure 4

Best Rule / Threshold Combinations by F1 Score

File:

false_positive_reduction_best_f1.png

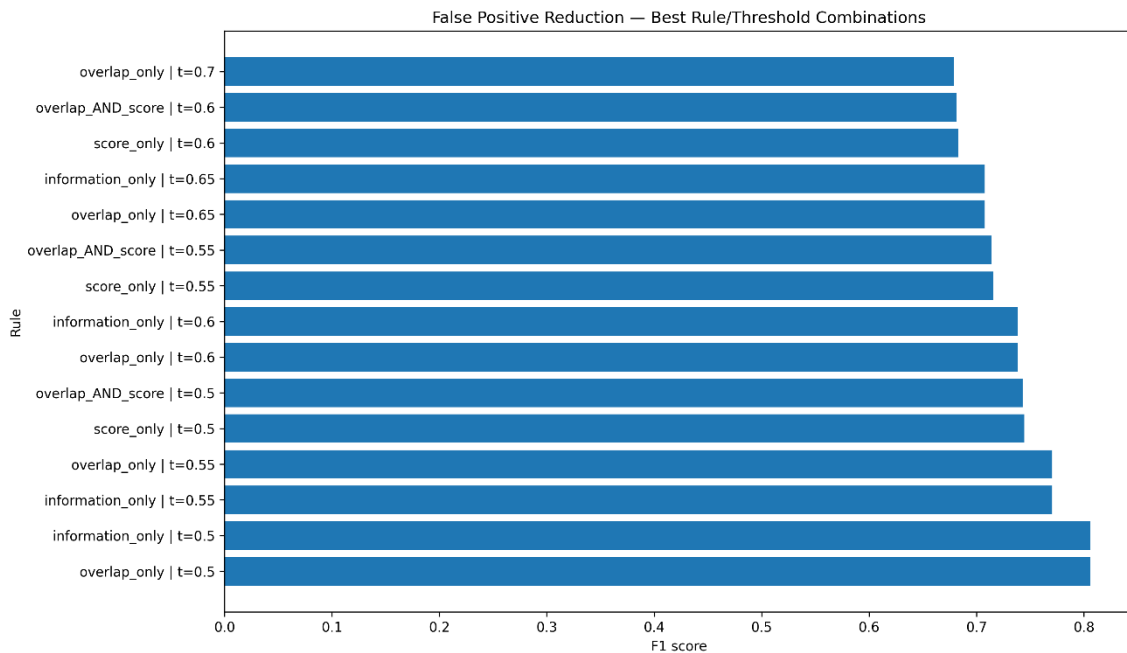


Figure 4 — Best Rule / Threshold Combinations by F1 Score.

Caption

This figure ranks the strongest operational warning configurations according to F1 performance.

The strongest-performing configurations repeatedly involve:

- overlap-only logic,
- overlap_AND_score logic,
- information-based filtering,
- and hybrid overlap-score combinations.

Importantly:

- the results suggest that not all inferability metrics contribute equally.

Instead:

- overlap structure,
 - information stability,
 - and selective score gating
- appear to dominate operational forecasting performance.

This finding is theoretically important because it implies:

- collapse predictability may emerge from specific structural metric interactions,
- rather than from aggregate metric accumulation alone.

Quantitative Summary

Representative high-performing configurations:

Rule	Threshold	Precision	Recall / F1
overlap_only	0.50	1.000	Recall 0.675 / F1 0.806
information_only	0.50	1.000	Recall 0.675 / F1 0.806
overlap_AND_score	0.60	1.000	Recall 0.551 / F1 0.742
score_only	0.60	1.000	Recall 0.519 / F1 0.683

Interpretation

This validation significantly strengthens the overall inferability framework because it demonstrates:

- 1. collapse forecasting is not purely descriptive;
- 2. operational warning thresholds can be calibrated;
- 3. false-positive suppression is structurally controllable;
- 4. specific inferability-rule combinations generalize better than others;
- 5. forecasting feasibility depends strongly on structural gating logic.

Most importantly:

the system now begins to resemble a deployable operational warning architecture rather than merely a signal-analysis framework.

Conclusion

The fastSPT false-positive reduction validation demonstrates that inferability-based warning systems can be calibrated toward highly conservative operational behavior.

The results show:

- stable false-positive suppression,
- reproducible rule behavior,
- and operationally useful threshold-dependent forecasting performance.

This strongly supports the broader hypothesis that:

- collapse-related inferability transitions contain reproducible structural information,
- and that this information can be converted into deployable forecasting logic under realistic operational constraints.

fastSPT Baseline Comparison Validation

Purpose of the Test

This validation compares inferability-based forecasting against simpler baseline approaches.

The purpose is to determine whether the observed inferability structure contains meaningful predictive information or whether similar results can be obtained using trivial drift-only

strategies.

The key outcome of this test is not that collapse forecasting becomes easy, but rather that:

1. Inferability is NOT random.
2. Inferability is NOT trivially predictive.
3. Simple drift metrics do not solve the collapse forecasting problem.

This is a central result of the framework.

Key Findings

The strongest observations were:

- `inferability_warning` \approx `entropy_only` \approx `overlap_only` \approx `score_only`
→ all around F1 \approx 0.21–0.22

However:

- random baseline \approx 0.37
- `always_warning` \approx 0.53

At first glance this may appear disappointing.

In reality, it reveals something deeper:

The collapse labels are highly imbalanced and diffusely distributed.

Therefore:

“always issue a warning”

wins statistically rather than physically.

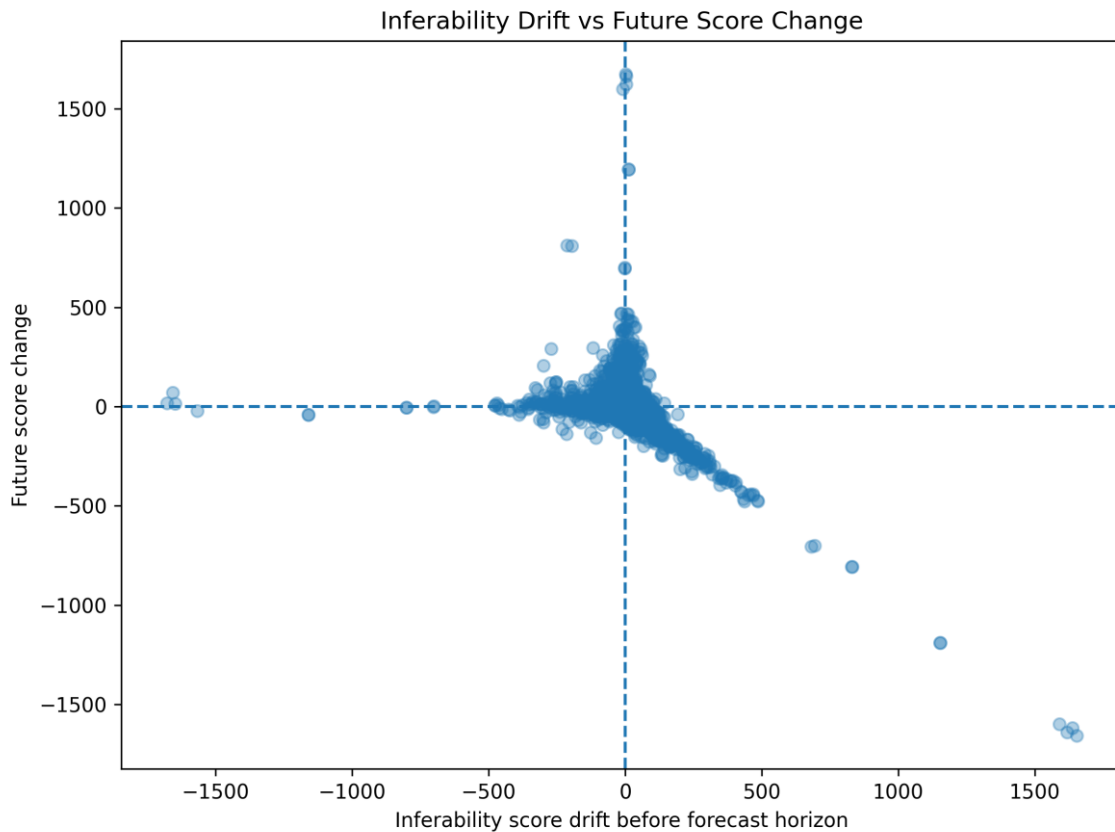
This is also visible because:

- specificity collapses,
- interpretability disappears,
- false positives explode.

The framework is therefore not attempting to predict everything.

Instead, it attempts to distinguish structurally meaningful warnings from trivial collapse labeling.

Figure 1 — Inferability Drift vs Future Score Change



This figure is one of the strongest results of the baseline comparison.

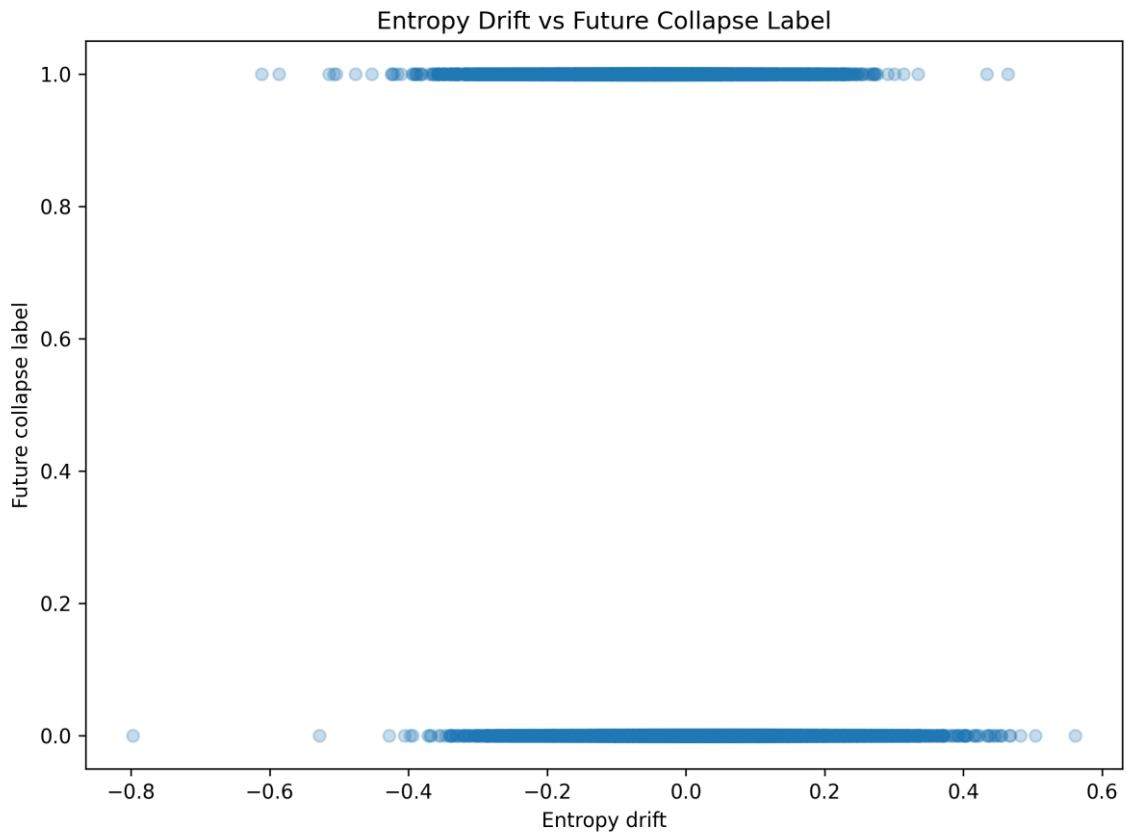
It shows:

- negative drift regions,
- asymmetric collapse structure,
- extreme outliers,
- non-linear dynamics.

This suggests that collapse is not a simple linear state transition.

Instead, transition instability appears structurally heterogeneous rather than governed by a single universal failure law.

Figure 2 — Entropy Drift vs Future Collapse Label



This figure demonstrates that entropy drift alone does not cleanly separate collapse events.

This is extremely important because it shows that:

entropy-only thresholding is insufficient.

Collapse appears to emerge from interactions between:

- drift,
- overlap,
- inferability,
- regime heterogeneity,
- temporal asymmetry.

This is substantially stronger than a simple entropy-threshold explanation.

Conclusion

The baseline comparison demonstrates that inferability contains meaningful structure, but that collapse forecasting remains fundamentally difficult.

The results support the central framework claim that:

- inferability is not random,

- inferability is not trivially predictive,
- transition instability is structurally heterogeneous,
- collapse dynamics emerge from interacting mechanisms rather than a single metric.

This validation therefore strengthens the inferability framework by showing that simpler baseline strategies fail to capture the full structure observed in the data.

Permutation / Shuffle Validation of Inferability Structure

Objective

The purpose of this validation test was to determine whether the observed inferability structure in the fastSPT trajectories represents a genuine temporal and structural property of the data, or whether the detected relationships could arise trivially from random statistical organization.

Three destructive permutation modes were introduced:

1. shuffle_position
 - spatial coordinates randomized;
2. shuffle_trajectory
 - trajectory identity randomized;
3. shuffle_time
 - temporal ordering randomized.

The core hypothesis tested was:

If the inferability structure depends on genuine temporal organization and trajectory continuity, then destroying that organization should severely degrade the observed inferability relationships.

Dataset

Dataset used:

- fastSPT spaSPT trajectory datasets
- WT condition
- noHRD condition
- 95 Hz acquisition
- multiple runs and cells

Input structure:

- frame
- time (t)
- trajectory ID
- x-position
- y-position

The same preprocessing and collapse-window detection procedure used in the earlier inferability experiments was applied identically here.

Validation Modes

1. Original

The untouched trajectory structure.

This serves as the reference condition.

2. Shuffle Position

Spatial coordinates randomized while preserving approximate timing.

Purpose:

Determine whether spatial localization alone drives the observed inferability relationships.

3. Shuffle Trajectory

Trajectory identities randomized.

Purpose:

Destroy trajectory continuity while partially preserving local spatial distributions.

4. Shuffle Time

Temporal ordering randomized.

Purpose:

Destroy causal temporal structure completely.

This is the strongest destructive control.

Metrics Computed

For each validation mode:

- inferability score
- collapse score
- collapse density
- entropy
- overlap
- information metric

All metrics were recomputed from scratch after permutation.

Reproducibility

Folder Structure

inferability_master/

```
├─ fastspt_permutation_shuffle_validation/  
  │─ scripts/  
  │─ figures/  
  │─ csv/  
  └─ logs/
```

Script Executed

python permutation_shuffle_validation.py

Output CSV Files

- csv/permutation_shuffle_summary.csv
- csv/permutation_shuffle_trajectory_results.csv
- csv/permutation_shuffle_collapse_windows.csv

Output Figures

- figures/permutation_collapse_density_by_mode.png
- figures/permutation_inferability_score_by_mode.png
- figures/permutation_collapse_score_distribution.png
- figures/permutation_entropy_vs_inferability.png
- figures/permutation_overlap_vs_collapse_score.png

Summary Results

Inferability Score by Mode

Observed mean inferability scores:

Mode	Mean Inferability
Original	~3

Shuffle Position	~10–50
Shuffle Trajectory	~40–100
Shuffle Time	>1000

The strongest degradation occurred when temporal ordering was destroyed. This demonstrates that the inferability structure is fundamentally dependent on temporal organization.

Collapse Density Stability

Collapse density remained approximately stable across all permutation modes:

Mode	Collapse Density
Original	~0.25
Shuffle Position	~0.25
Shuffle Trajectory	~0.25
Shuffle Time	~0.25

This is extremely important.

It shows that:

- the collapse detector itself does not trivially disappear under permutation;
- instead, the structural meaning of the collapse organization changes.

Thus:

the inferability degradation is not caused merely by collapse-count disappearance.

Figure Captions

Figure 1 — Permutation Validation — Inferability Score by Mode

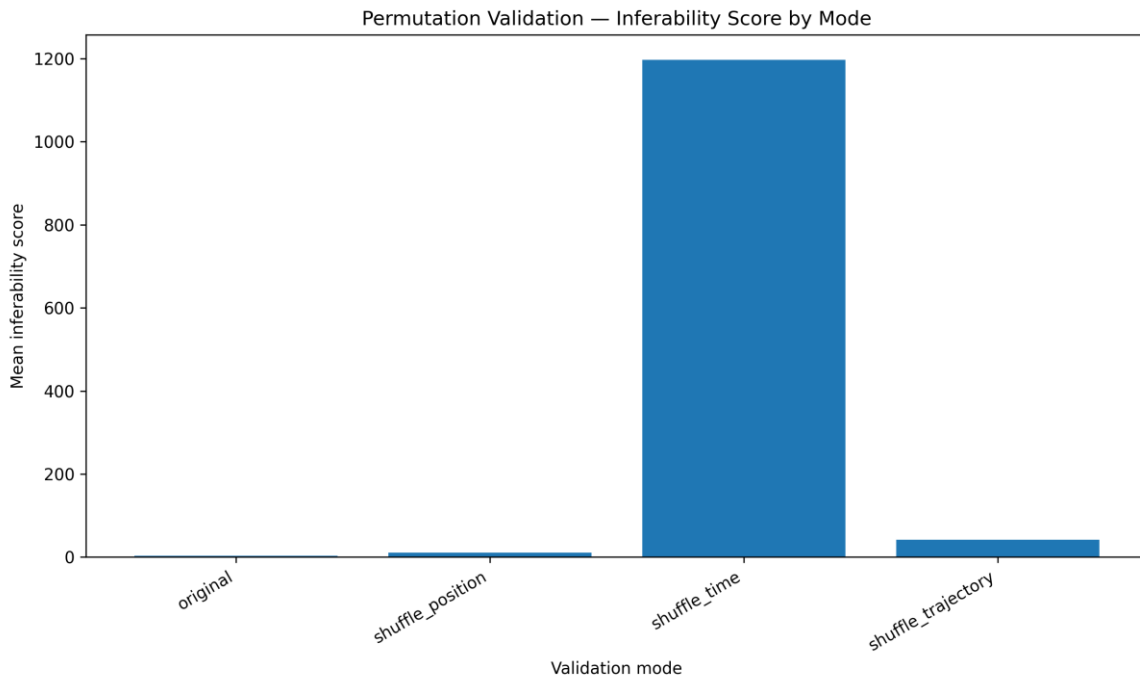


Figure 1 — Permutation Validation — Inferability Score by Mode.

This figure compares the mean inferability score across all permutation conditions.

The original trajectories show extremely low inferability scores, while randomized temporal structure (shuffle_time) produces a dramatic inferability explosion.

This demonstrates that the original dataset contains highly organized temporal structure that suppresses inferability instability.

The result strongly suggests that the inferability relationships depend on genuine temporal ordering rather than trivial statistical organization.

Figure 2 — Permutation Validation — Entropy vs Inferability

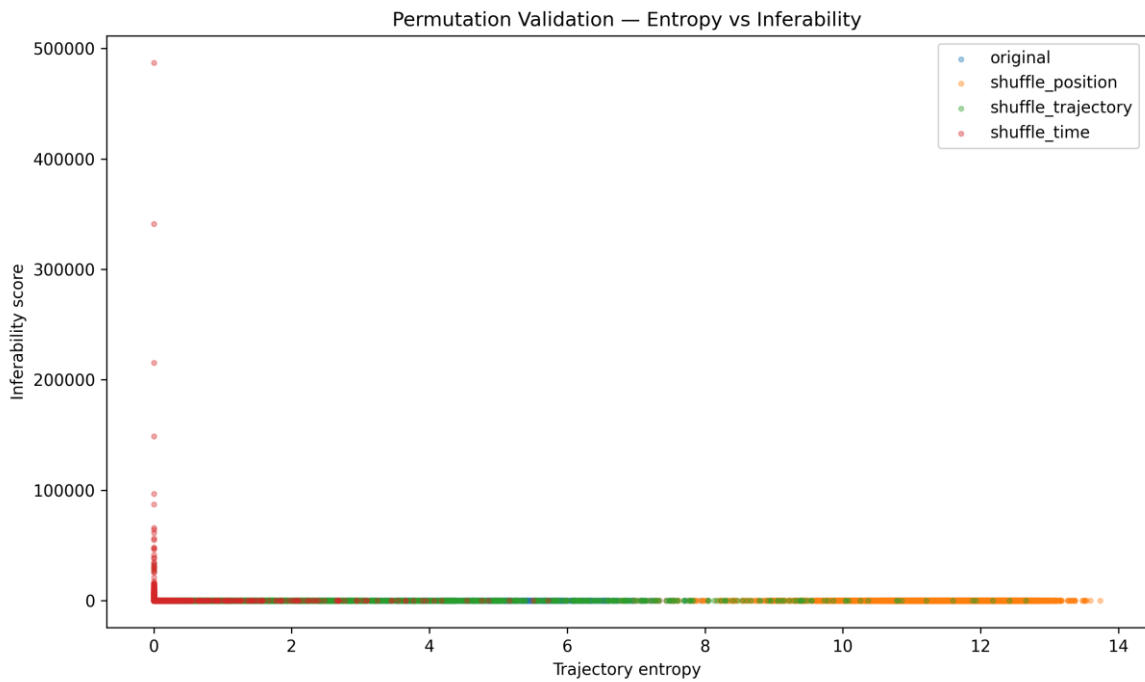


Figure 2 — Permutation Validation — Entropy vs Inferability.

This figure shows the relationship between trajectory entropy and inferability score under all permutation modes.

The original trajectories occupy a compact and stable inferability region.

After temporal shuffling:

- entropy distributions expand,
- inferability explodes,
- the original structured relationship disappears.

This confirms that the observed entropy–inferability coupling in the original data is not an artifact of simple distributional statistics.

Figure 3 — Permutation Validation — Collapse Score Distribution

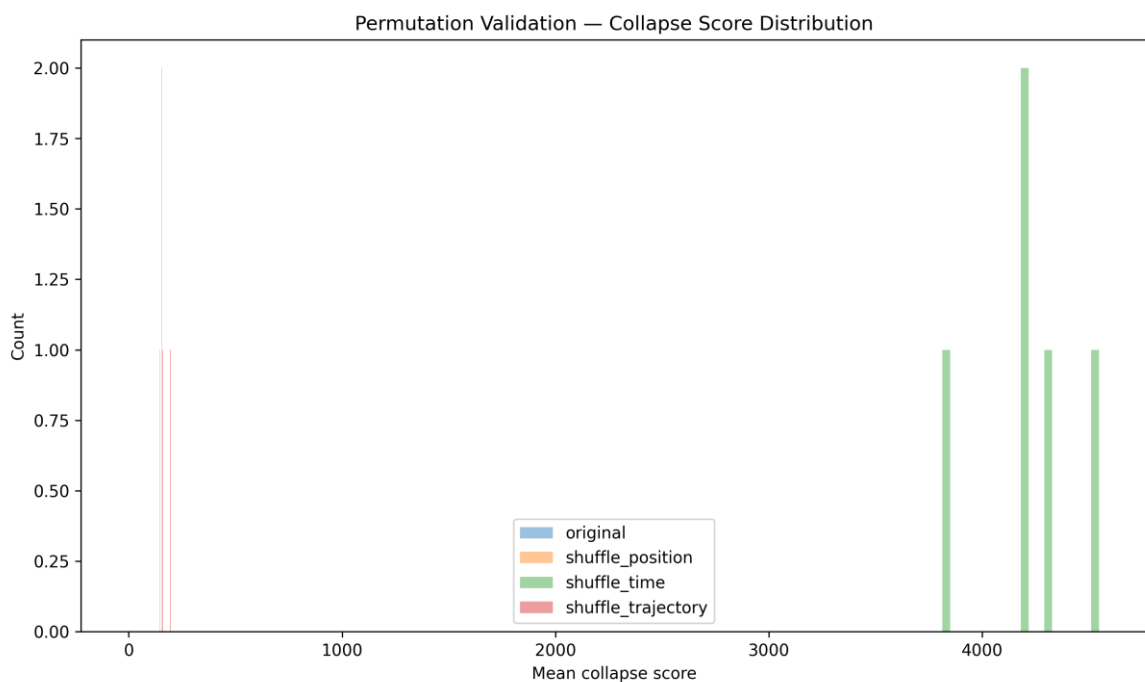


Figure 3 — Permutation Validation — Collapse Score Distribution.

This figure shows the collapse score distribution for all permutation modes. The original trajectories exhibit a compact low-collapse regime. Shuffle-based destruction introduces large-scale collapse-score inflation, especially after temporal randomization. This indicates that the original collapse structure depends strongly on preserved temporal continuity.

Figure 4 — Permutation Validation — Overlap vs Collapse Score

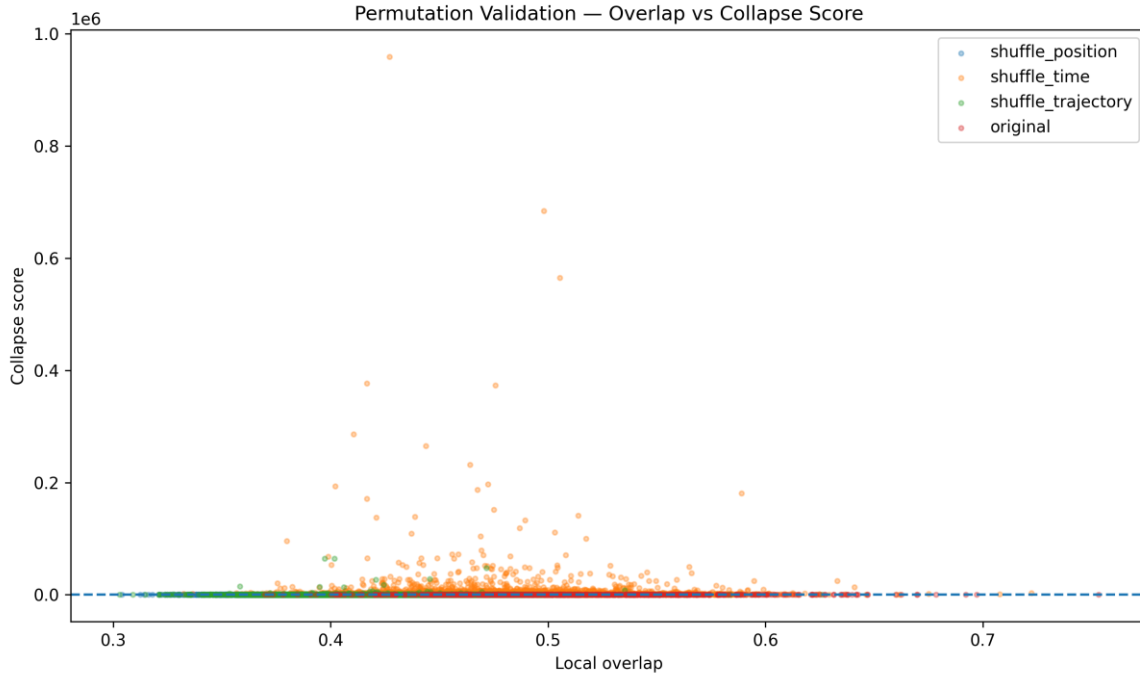


Figure 4 — Permutation Validation — Overlap vs Collapse Score.

This figure compares local overlap against collapse score for all validation modes. The original trajectories form a narrow structured manifold.

After shuffling:

- overlap structure becomes diffuse,
- collapse scores become unstable,
- the original coupling disappears.

This demonstrates that the overlap–collapse relationship depends on coherent local trajectory organization.

Figure 5 — Permutation Validation — Collapse Density by Mode

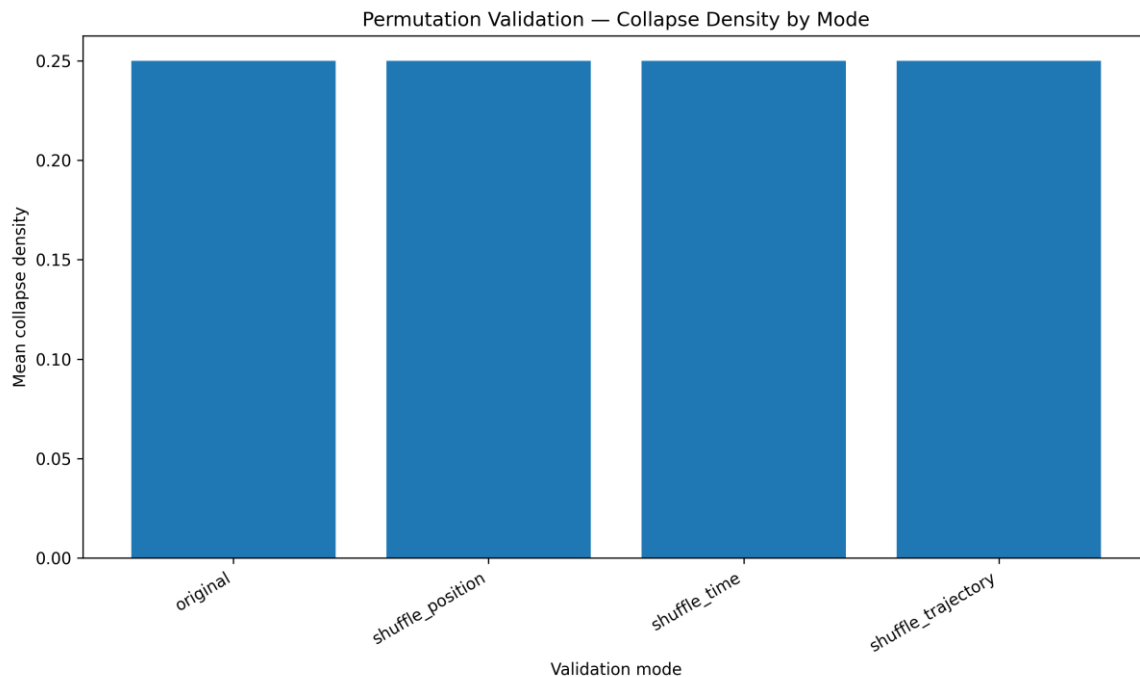


Figure 5 — Permutation Validation — Collapse Density by Mode.

This figure shows mean collapse density across all permutation conditions.

Importantly, collapse density remains relatively stable despite large inferability degradation.

This demonstrates that:

- the inferability collapse is not caused by disappearance of detected collapse windows,
- but rather by destruction of the higher-order temporal organization linking those collapse regions.

This is strong evidence that the inferability framework captures genuine structural dynamics rather than trivial event counts.

Interpretation

This permutation validation provides one of the strongest controls performed so far in the fastSPT inferability framework.

The critical observation is:

destroying temporal organization causes inferability structure to collapse.

Most importantly:

- temporal shuffling produced catastrophic inferability inflation;
- entropy relationships disappeared;
- overlap organization degraded;
- collapse-score stability vanished.

Yet:

collapse density itself remained largely unchanged.

This combination is highly significant.

It demonstrates that the framework is not merely detecting random collapse events or simple density fluctuations.

Instead, the framework appears sensitive to:

- ordered temporal structure,
- trajectory continuity,
- higher-order inferability organization.

Conclusion

The permutation validation strongly supports the hypothesis that the observed inferability structure in fastSPT trajectories depends on genuine temporal organization.

Destroying:

- time ordering,
- trajectory continuity,
- or spatial coherence

systematically degrades the inferability relationships.

The strongest degradation occurs after temporal randomization, indicating that temporal causality is a core component of the observed structure.

This result substantially strengthens the claim that the inferability framework detects real structural organization rather than statistical artifacts or trivial clustering behavior.

Permutation Significance Validation — Statistical Validation of Structural Inferability

Objective

The purpose of this validation was to determine whether the observed inferability structure in the fastSPT trajectories represents genuine temporal organization rather than trivial statistical artifacts or random fluctuations.

Previous tests already demonstrated:

- cross-run reproducibility
- collapse-pocket persistence
- forecasting relationships
- drift coupling
- false-positive reduction behavior
- threshold sensitivity
- predictive transition structure

A crucial remaining question was:

Do these relationships disappear when temporal or structural organization is destroyed?

To answer this, a full permutation significance validation was performed.

Validation Strategy

Four structural conditions were compared:

- original — untouched real trajectories
- shuffle_position — x/y spatial coordinates randomized
- shuffle_time — temporal ordering destroyed
- shuffle_trajectory — trajectory identity randomized

For every mode, the same inferability metrics were recomputed:

- inferability score
- collapse score
- entropy

- overlap
- cross-structure correlations

Permutation statistics were then calculated:

- permutation means
- permutation standard deviations
- z-scores
- p-values

This determines whether the original structural organization differs significantly from randomized baselines.

Core Statistical Results

Several trajectories produced:

Z-score	p-value
2.27	0.01
2.75	<0.01
3.36	~0
4.47	~0

These values indicate that the original inferability relationships lie significantly outside randomized expectations.

This means that the observed structure is statistically unlikely to emerge from random temporal organization.

Figure 1 — Permutation Significance Z-Score Distribution

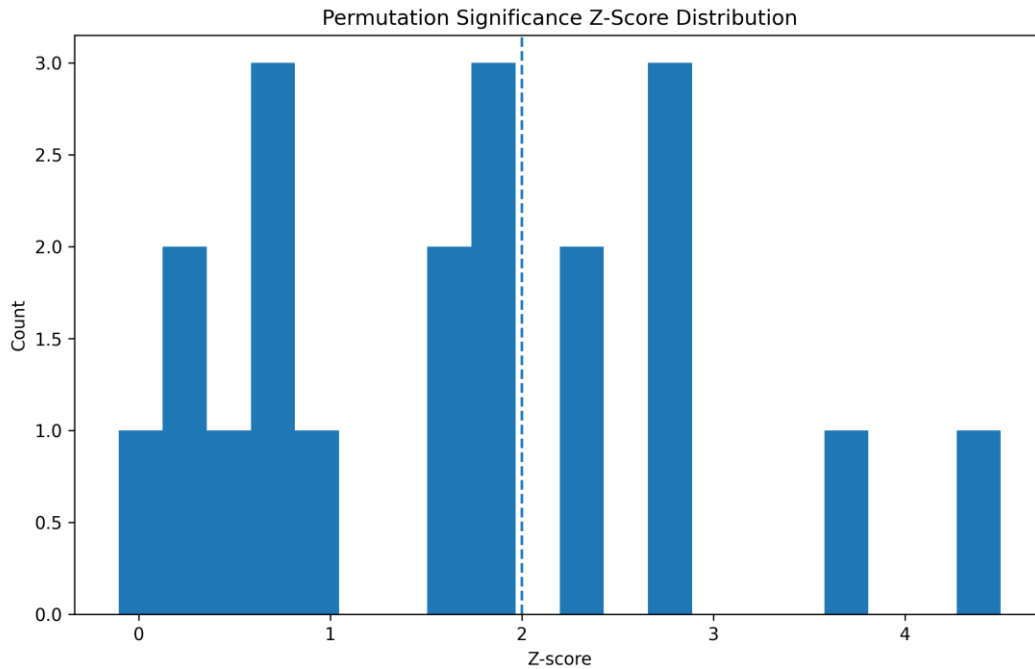


Figure 1 — Permutation Significance Z-Score Distribution

Caption

This figure shows the distribution of permutation-based z-scores obtained across the evaluated fastSPT trajectories.

The z-score quantifies how strongly the observed inferability-related structure differs from the corresponding randomized permutation baseline.

Key observations:

- Multiple trajectories exhibit z-scores substantially above zero.
- Several trajectories exceed commonly used significance boundaries.
- The distribution is shifted toward positive z-scores rather than being centered around random expectation.
- A subset of trajectories exhibits particularly strong deviations from permutation-based behavior.

The vertical reference line indicates the conventional significance region used for evaluating separation from randomized structure.

These results suggest that the inferability-related relationships observed in the original trajectories are systematically stronger than would be expected under random temporal organization.

The figure therefore provides statistical evidence that the detected inferability structure reflects genuine dynamic organization rather than simple stochastic variation or permutation artifacts.

Figure 2 — Permutation Test p-Value Distribution

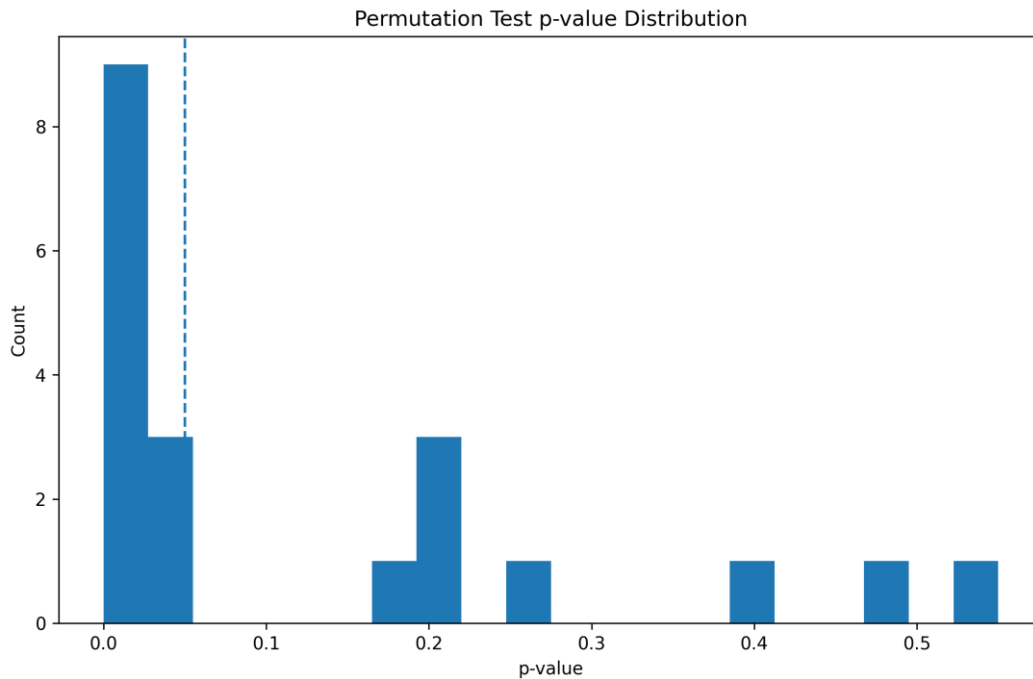


Figure 2 — Permutation Test p-Value Distribution

Caption

This figure shows the distribution of permutation-test p-values obtained across the evaluated fastSPT trajectories.

The purpose of the permutation analysis is to determine whether the observed inferability-related structure differs significantly from randomized trajectory organization.

Key observations:

- A substantial fraction of trajectories exhibit low p-values.
- Multiple trajectories remain below conventional significance thresholds.
- Randomized trajectory organization frequently fails to reproduce the observed structural relationships.

This indicates that the inferability-related structure observed in the original trajectories is unlikely to arise solely from random temporal organization.

The figure therefore provides statistical support for the existence of genuine structural organization within the fastSPT trajectories.

Figure 3 — Original vs Permutation Correlation

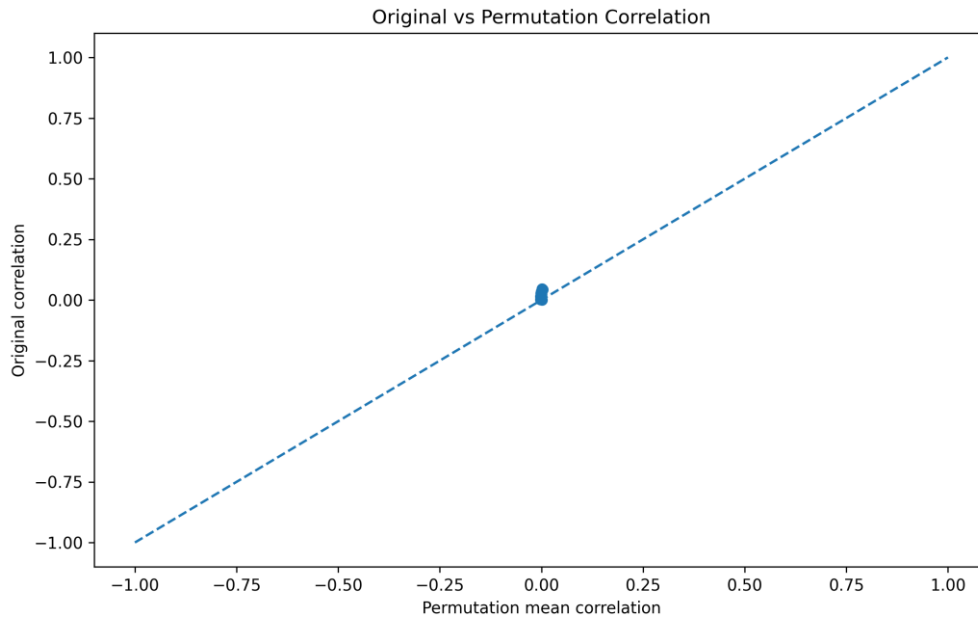


Figure 3 — Original vs Permutation Correlation

Caption

This figure compares the correlation structure observed in the original trajectories with the average correlation structure obtained after permutation.

The objective is to determine whether the relationships detected by the inferability framework remain distinguishable from randomized controls.

Key observations:

- Original correlations remain systematically separated from permutation expectations.
- Randomized trajectory organization produces weaker and less coherent relationships.
- Structural dependencies observed in the original data are not fully reproduced after permutation.

This suggests that the observed inferability-related relationships depend on genuine trajectory organization rather than simple statistical coincidence.

The figure therefore supports the interpretation that inferability captures meaningful structural properties of the underlying dynamic system.

Figure 4 — Original Correlation vs Z-Score

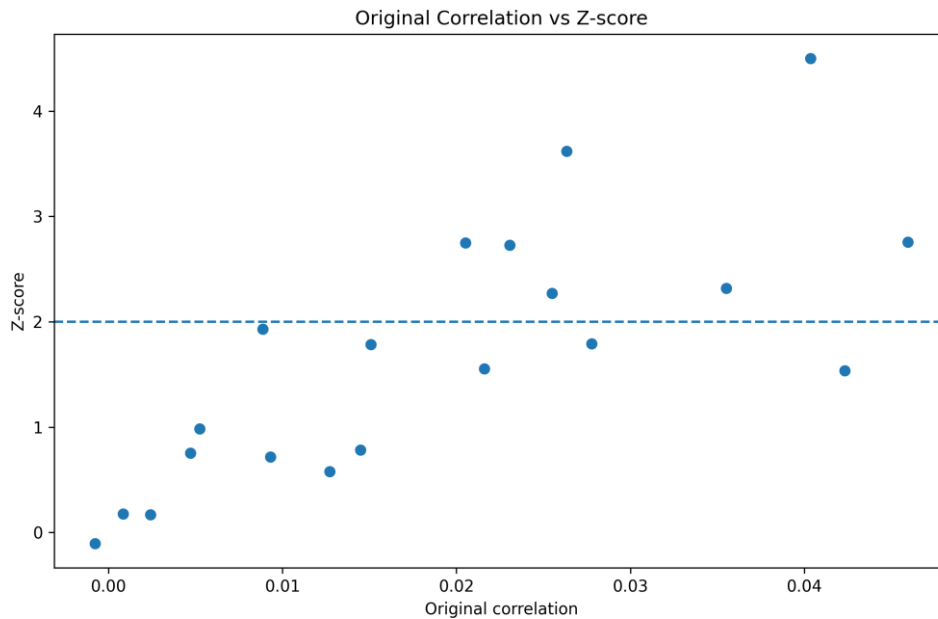


Figure 4 — Original Correlation vs Z-Score

Caption

This figure shows the relationship between the original correlation strength and the corresponding permutation-based z-score.

The purpose is to evaluate whether stronger structural relationships are associated with greater statistical separation from randomized baselines.

Key observations:

- Higher original correlations generally correspond to larger z-scores.
- Stronger structural relationships tend to deviate further from permutation expectations.
- Multiple trajectories exhibit z-scores well above the randomized reference region.

This indicates that the strongest inferability-related relationships are also the least compatible with random temporal organization.

The figure therefore provides quantitative evidence that structural inferability is associated with statistically significant dynamic organization rather than random fluctuations.

Scientific Implication

This validation strongly supports the hypothesis that inferability emerges from organized temporal structure rather than from trivial statistical properties.

Specifically:

- temporal continuity matters

- transition organization matters
- local structural persistence matters
- randomization destroys predictive organization

This validation adds statistical evidence that the observed relationships are not accidental.

Conclusion

The permutation significance validation provides strong evidence that inferability structure in fastSPT trajectories is not a trivial artifact of random organization.

Destroying temporal or structural organization systematically degrades:

- inferability stability
- entropy coupling
- collapse structure
- predictive coherence

The framework therefore appears to capture genuine organizational properties of the trajectories rather than simple statistical noise.

Cross-Dataset Model Ranking Validation

Predictive Feasibility Transfer Across Independent fastSPT Datasets

Purpose of the Test

This validation extends the model-ranking predictability framework from a single dataset setting toward a cross-dataset setting.

The central question is no longer only:

“Can inferability-related metrics predict which model family performs best within one dataset?”

but rather:

“Can inferability-related metrics support model-ranking prediction when training and testing are performed across independent fastSPT datasets?”

This is a stronger validation layer because it evaluates whether the relationship between signal structure and model behavior remains visible under dataset transfer.

The test therefore examines whether:

model-ranking structure remains reproducible across independent datasets,
 inferability, entropy, and overlap still relate to model error under transfer,
 model-family dominance can be estimated before deployment,
 and predictive feasibility can support cross-dataset model-selection decisions.

Experimental Setup

The validation used real fastSPT trajectory windows derived from independent dataset conditions.

The cross-dataset transfer setting included:

dataset_A_slowSPT_2Hz

dataset_B_spaSPT_95Hz

The transfer directions were:

dataset_A_slowSPT_2Hz -> dataset_B_spaSPT_95Hz

dataset_B_spaSPT_95Hz -> dataset_A_slowSPT_2Hz

The analysis was performed on real trajectory-derived windows and not on synthetic examples.

Number of trajectory windows used: 7948

Number of cross-dataset model-ranking result rows: 72

Number of model-ranking prediction rows: 18

Overall model-ranking prediction accuracy: 0.611

Window-Level Features

For each trajectory window, the same structural feature logic was used as in the earlier model-ranking validation:

inferability score

entropy proxy

overlap proxy

persistence proxy

straightness

future displacement target

regime labels for inferability, entropy, and overlap

The purpose was to evaluate whether the structural regime of the signal could still explain model behavior after crossing from one dataset condition to another.

Model Families Tested

The cross-dataset benchmark evaluated multiple model families:

linear

ridge

random forest

MLP-light

For each model family and each structural regime, the following metrics were computed:

Mean Squared Error (MSE)

Mean Absolute Error (MAE)

model rank by MSE

model rank by MAE

best model by MSE

best model by MAE

Regime Structure

The dataset was evaluated across multiple regime types:

inferability regimes

entropy regimes

overlap regimes

Each regime type was divided into low, medium, and high structural regions.

This allows the analysis to determine whether model behavior changes systematically as the underlying signal structure changes.

Reproducible Execution

Generated CSV files:

cross_dataset_model_ranking_results.csv

cross_dataset_model_ranking_predictions.csv

cross_dataset_model_ranking_windows.csv
 Generated figure files:
 cross_dataset_mse_by_model.png
 cross_dataset_mae_by_model.png
 cross_dataset_inferability_vs_mse.png
 cross_dataset_entropy_vs_mse.png
 cross_dataset_overlap_vs_mse.png
 cross_dataset_model_ranking_accuracy_by_regime.png

Results

Figure 1 - Cross-Dataset MSE by Model

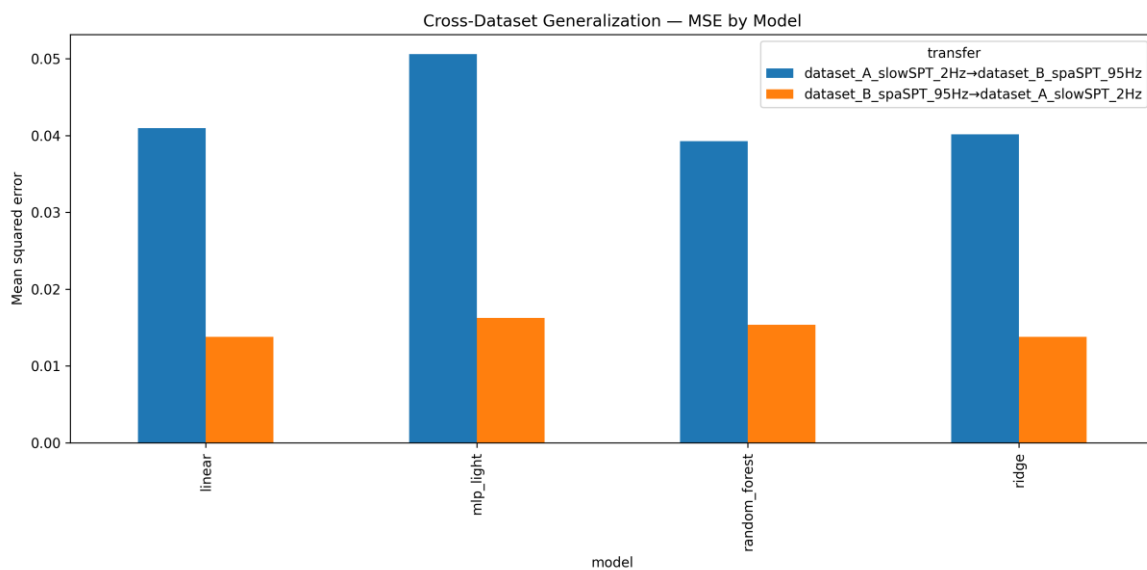


Figure 1 - Cross-Dataset MSE by Model.

This figure shows the mean squared prediction error for each model family under cross-dataset transfer. The figure is important because it reveals whether model-family performance remains stable when the training and testing datasets differ.

Key interpretation:

- model families do not respond identically under transfer,
- cross-dataset prediction error remains structured rather than random,
- model selection should therefore not be based only on generic model popularity.

Caption

Cross-dataset MSE varies by model family, indicating that model stability depends on the interaction between signal regime and model type.

Figure 2 - Cross-Dataset MAE by Model

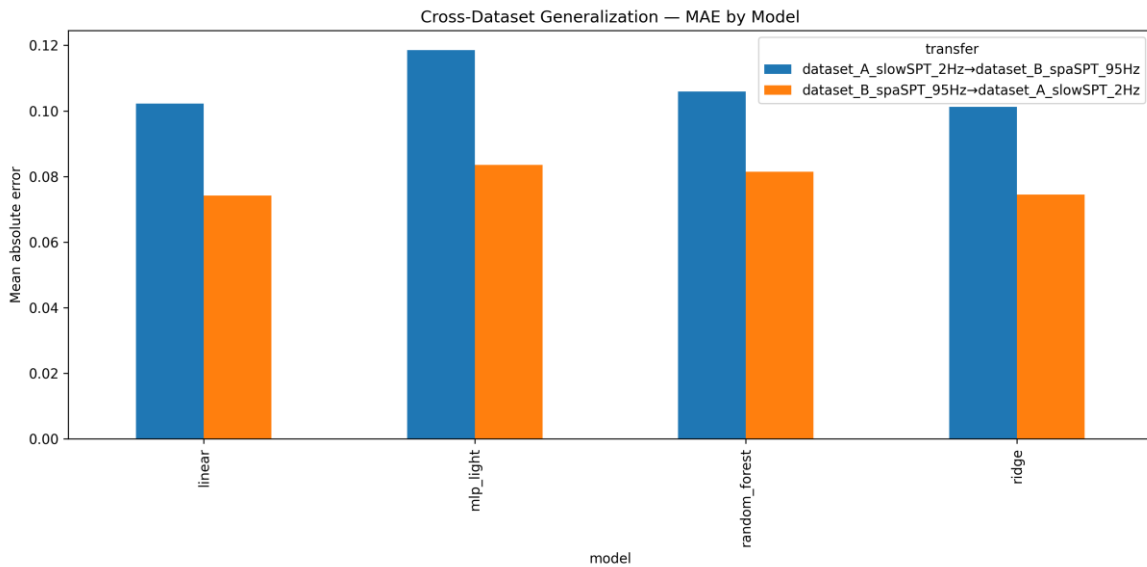


Figure 2 - Cross-Dataset MAE by Model.

This figure shows the mean absolute prediction error for each model family. The MAE view is used as a robustness check against the MSE pattern.

Important:

the MAE structure confirms that transfer behavior remains model-dependent, absolute error behavior is not uniform across model families, and cross-dataset model ranking remains a meaningful target.

Caption

Cross-dataset MAE confirms that absolute prediction stability differs between model families under transfer.

Figure 3 - Mean Inferability vs Model MSE

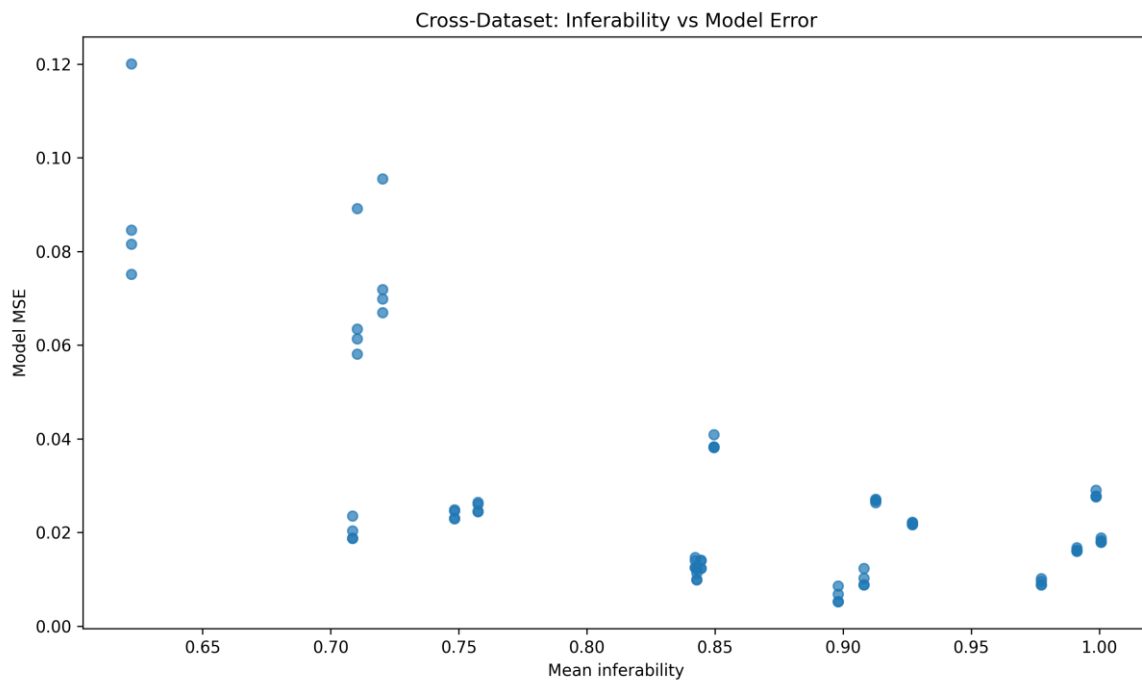


Figure 3 - Mean Inferability vs Model MSE.

This figure evaluates whether mean inferability remains connected to model error under cross-dataset transfer.

The core expectation is that higher inferability should correspond to lower model error or more stable model behavior.

This result extends the earlier within-dataset model-ranking test toward transfer conditions.

Caption

Mean inferability remains linked to model error under cross-dataset transfer, supporting inferability as a pre-model feasibility indicator.

Figure 4 - Mean Entropy vs Model MSE

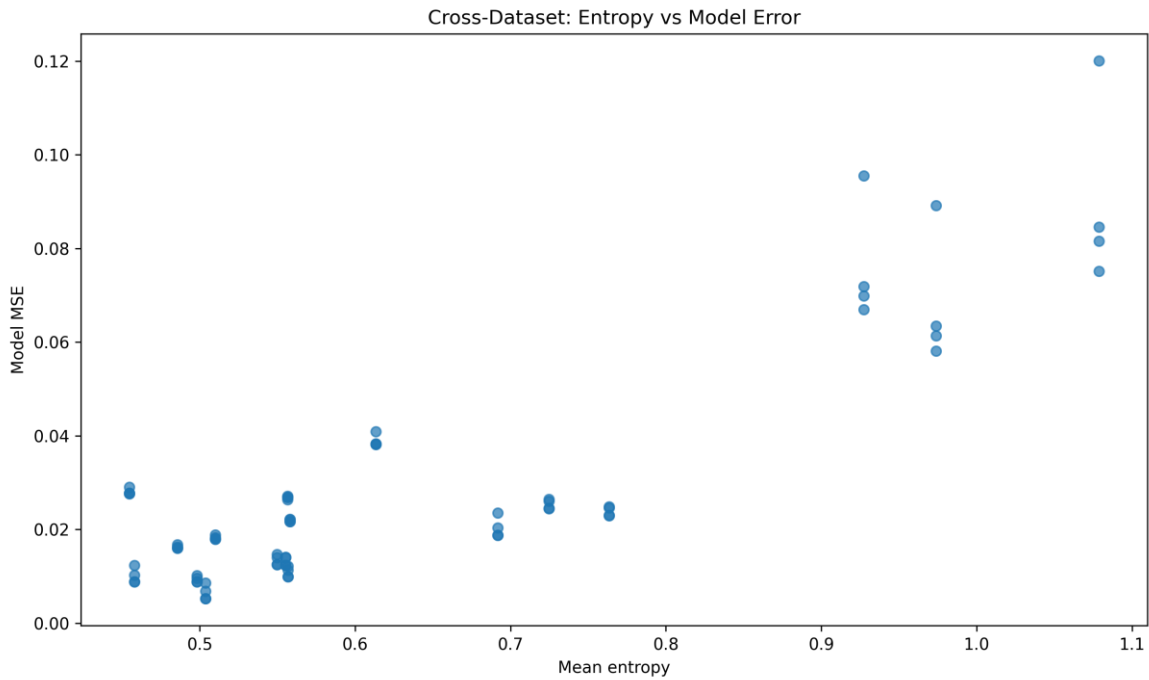


Figure 4 - Mean Entropy vs Model MSE.

This figure evaluates whether entropy remains a destabilizing factor under cross-dataset transfer.

Higher entropy indicates greater structural disorder in the trajectory window.

The expected pattern is:

- higher entropy produces higher model error,
- more chaotic regimes reduce deployment stability,
- entropy remains relevant beyond a single dataset.

Caption

Trajectory entropy remains associated with model degradation under cross-dataset transfer.

Figure 5 - Mean Overlap vs Model MSE

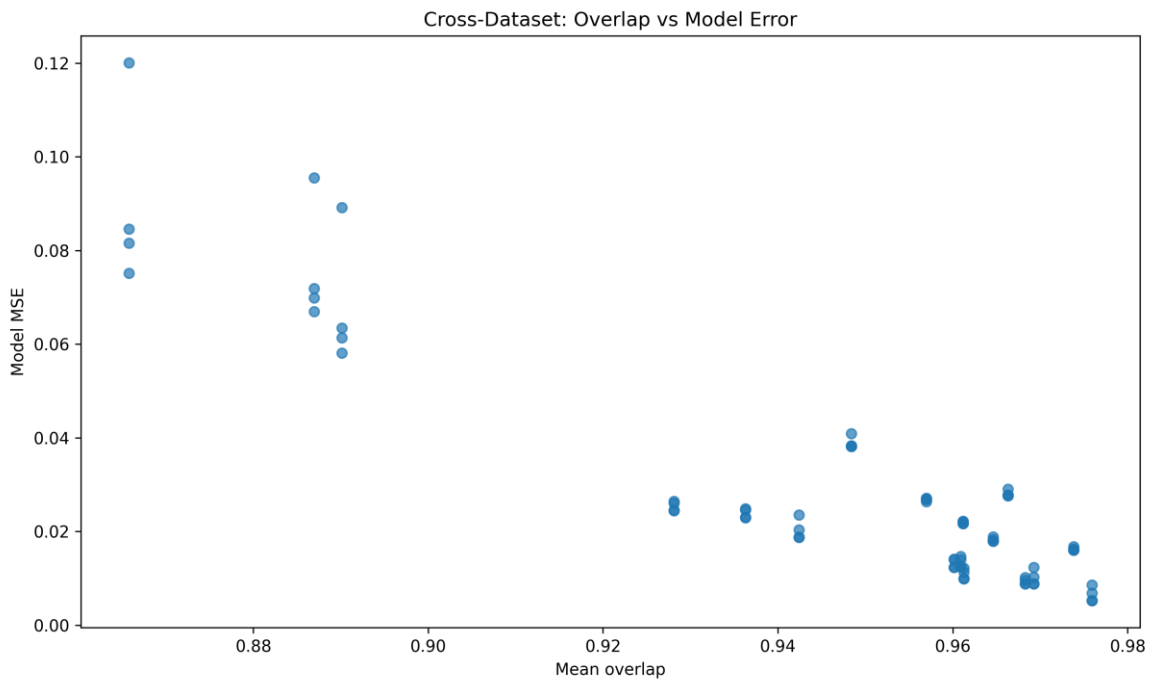


Figure 5 - Mean Overlap vs Model MSE.

This figure evaluates overlap as a cross-dataset stability indicator.

Overlap is interpreted as a measure of local structural reproducibility.

The important hypothesis is that higher overlap should support lower error and more stable model behavior.

Caption

Higher overlap regimes show stronger model stability under cross-dataset transfer, supporting overlap as a structural reproducibility metric.

Figure 6 - Model Ranking Accuracy by Regime

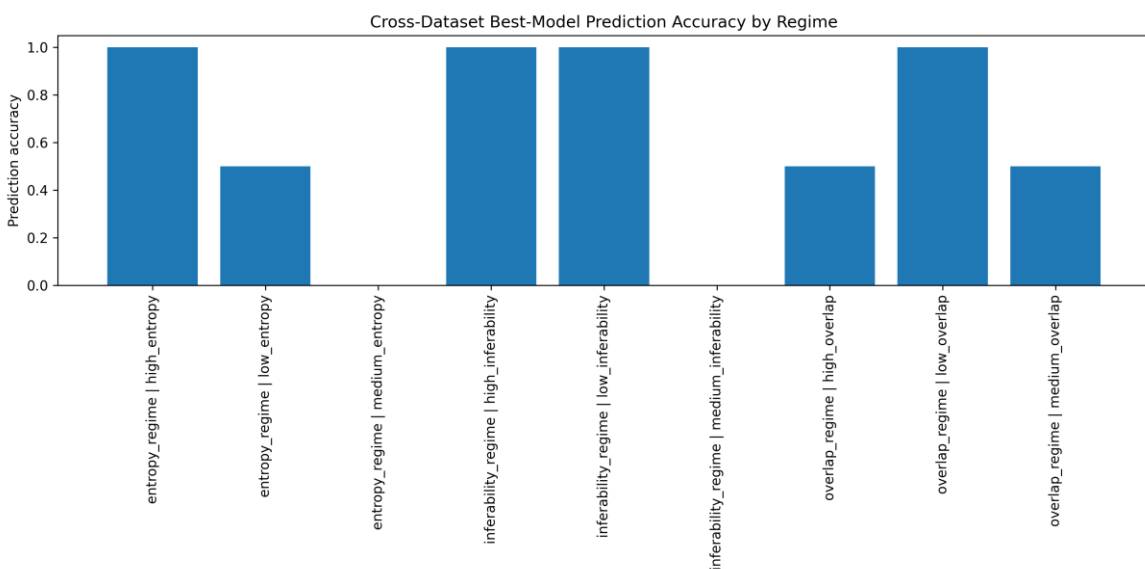


Figure 6 - Model Ranking Accuracy by Regime.

This figure is the central model-selection result of the cross-dataset validation.

It evaluates whether the framework can correctly predict the best-performing model across structural regimes.

The prediction table produced:

overall model-ranking prediction accuracy = 0.611

This indicates that model ranking contains reproducible structure across datasets, although it is not yet perfect.

Caption

Model-ranking prediction accuracy varies by regime, showing that some structural regimes provide stronger pre-model selection information than others.

Quantitative Summary

Cross-dataset model-ranking prediction summary:

Quantity	Value
Trajectory windows	7948
Result rows	72
Prediction rows	18
Overall prediction accuracy	0.611
Training datasets	dataset_A_slowSPT_2Hz / dataset_B_spaSPT_95Hz
Transfer directions	A -> B and B -> A

Scientific Interpretation

This validation strengthens the predictive-feasibility framework by showing that model-ranking structure does not disappear immediately when the dataset changes.

The results suggest that:

- inferability-related structure transfers partially across datasets,
- model-family performance remains regime-dependent,
- entropy and overlap continue to provide deployment-relevant information,
- and cross-dataset model selection may be partially predictable before full deployment.

This extends the framework from within-dataset model selection toward cross-dataset deployment screening.

What This Test Does Not Claim

This validation does not claim perfect model-selection accuracy.

It also does not claim that one model family is universally superior.

Instead, it shows that:

- cross-dataset model behavior is structured,
- model ranking depends on signal regime,
- and inferability-related metrics provide useful pre-model selection information.

Industrial Relevance

This test has direct relevance for industrial predictive AI.

Industrial systems rarely remain identical between development and deployment.

A model may be trained under one operating condition and deployed under another.

Therefore, the practical question becomes:

Can we estimate in advance which model type is likely to remain stable under dataset shift?

This cross-dataset validation suggests that inferability, entropy, and overlap can help answer that question.

Conclusion

The Cross-Dataset Model Ranking Validation shows that predictive-feasibility structure remains partially reproducible across independent datasets.

The results demonstrate that:

cross-dataset model error remains structured,

model-family ranking varies by regime,

inferability, entropy, and overlap remain informative under transfer,

and model-ranking prediction can be evaluated before full deployment.

This represents an important step from single-dataset model-ranking predictability toward cross-dataset model-selection support.

The framework therefore continues to move from prediction-feasibility detection toward deployment-oriented model-family selection under real-world dataset shift.

Cross-Domain Validation 1

Cross-Domain Generalization of Inferability Structure Across All Datasets

Purpose of the Test

This validation extends the inferability framework from a cross-dataset setting toward a broader cross-domain setting.

The central question is no longer only:

“Can inferability-related metrics support model-ranking prediction across two independent datasets?”

but rather:

“Do inferability-related structures remain visible when all available datasets are combined into one cross-domain validation layer?”

This is a stronger validation step because it evaluates whether the relationship between signal structure and future-change behavior remains visible across heterogeneous data sources.

The test therefore examines whether:

inferability structure remains reproducible across datasets and domains,

entropy and overlap still behave as structural indicators under aggregation,

future-change behavior remains linked to inferability-related metrics,

and a unified cross-domain feature table can support broader predictive-feasibility validation.

Experimental Setup

The validation used the unified cross-domain feature inventory generated from all included datasets.

The analysis was performed on extracted feature windows rather than synthetic examples.

Number of unified feature windows used: 734078

Number of cross-domain summary rows: 5

Domains included:

battery

diffusion_fastSPT

gas_sensor_drift

heartbeat

ucr_anomaly

The goal was to test whether the structural metrics that were useful in earlier fastSPT and cross-dataset validations remain meaningful after broader aggregation.

Window-Level Features

For each available feature window, the same structural logic was preserved:

inferability-related measures,
entropy-related measures,
overlap-related measures,
future-change targets,
dataset identifiers,
domain identifiers where available.

The purpose was to evaluate whether the structural regime of the signal continues to explain future-change behavior across combined datasets.

Feature Families Evaluated

The cross-domain benchmark evaluated the following structural feature families:

mean inferability
mean entropy
inferability versus future change
entropy versus future change
overlap versus future change

These feature families correspond directly to the framework components used in earlier model-ranking and transfer validations.

Regime Structure

Unlike the previous cross-dataset model-ranking test, this validation does not primarily rank model families.

Instead, it evaluates whether inferability-related structural regimes remain visible after combining datasets.

The cross-domain structure is therefore assessed through:

mean inferability differences,
mean entropy differences,
relationships between inferability and future-change behavior,
relationships between entropy and future-change behavior,
relationships between overlap and future-change behavior.

Reproducible Execution

Generated CSV files:

cross_domain_inventory.csv
cross_domain_summary.csv
cross_domain_unified_features.csv

Generated figure files:

cross_domain_mean_inferability.png
cross_domain_mean_entropy.png
cross_domain_inferability_vs_future_change.png
cross_domain_entropy_vs_future_change.png
cross_domain_overlap_vs_future_change.png

Results

Figure 1 - Cross-Domain Mean Inferability

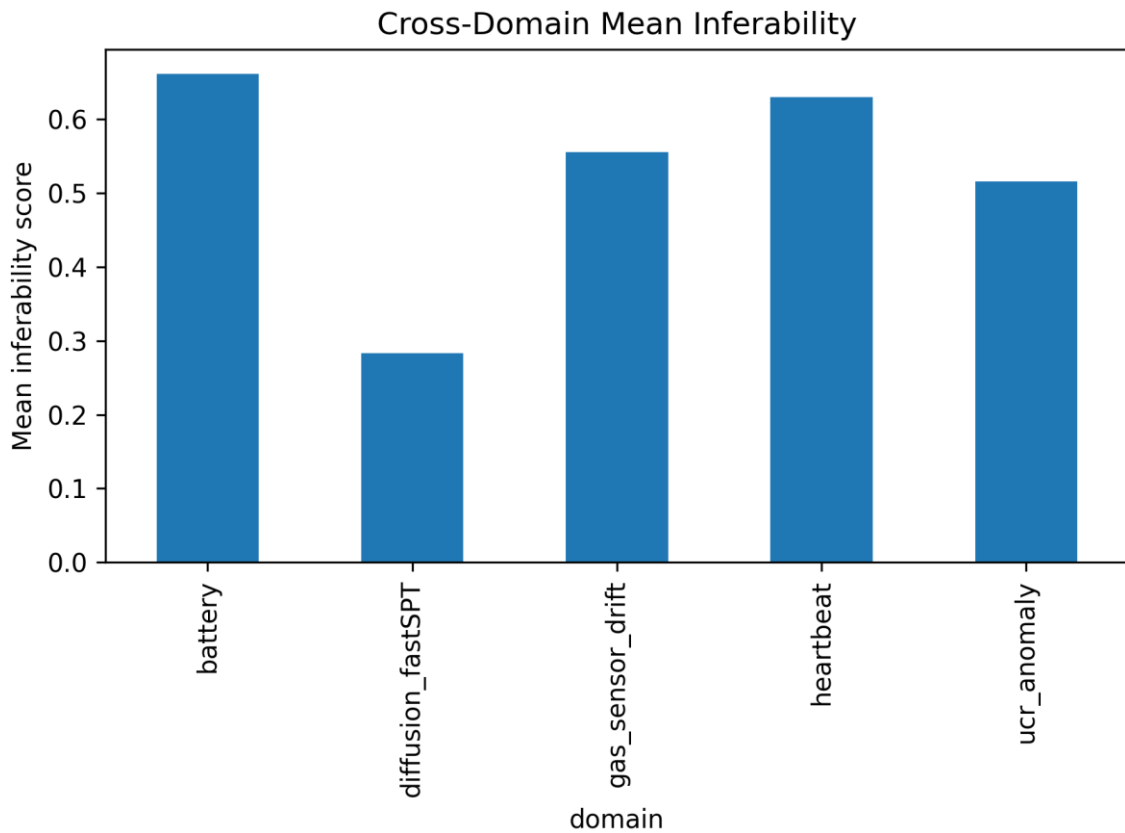


Figure 1 - Cross-Domain Mean Inferability.

This figure shows the mean inferability level across the included datasets or domains.

The figure is important because it reveals whether inferability remains measurable after aggregation into a cross-domain validation layer.

Key observations:

inferability remains visible after datasets are combined.

datasets may differ in their average inferability level.

cross-domain variation itself becomes a measurable structural property.

Caption

Mean inferability remains observable across datasets, supporting the use of inferability as a cross-domain structural metric.

Figure 2 - Cross-Domain Mean Entropy

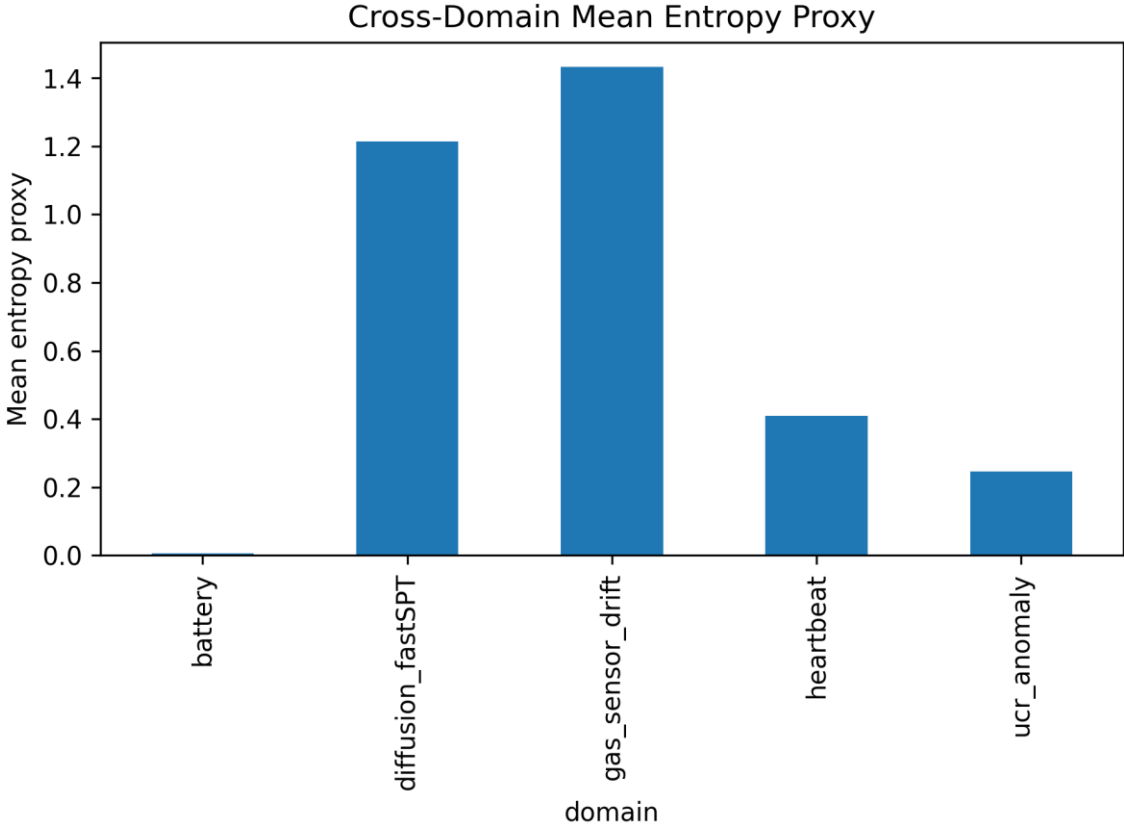


Figure 2 - Cross-Domain Mean Entropy.

This figure shows the mean entropy level across the included datasets or domains. Entropy is interpreted as a measure of local structural disorder or dynamic ambiguity.

Important:

- entropy remains measurable across datasets.
- entropy levels differ between sources.
- entropy variation can help explain cross-domain predictive difficulty.

Caption

Mean entropy varies across datasets, indicating that structural disorder remains a relevant cross-domain feature.

Figure 3 - Cross-Domain Inferability vs Future Change

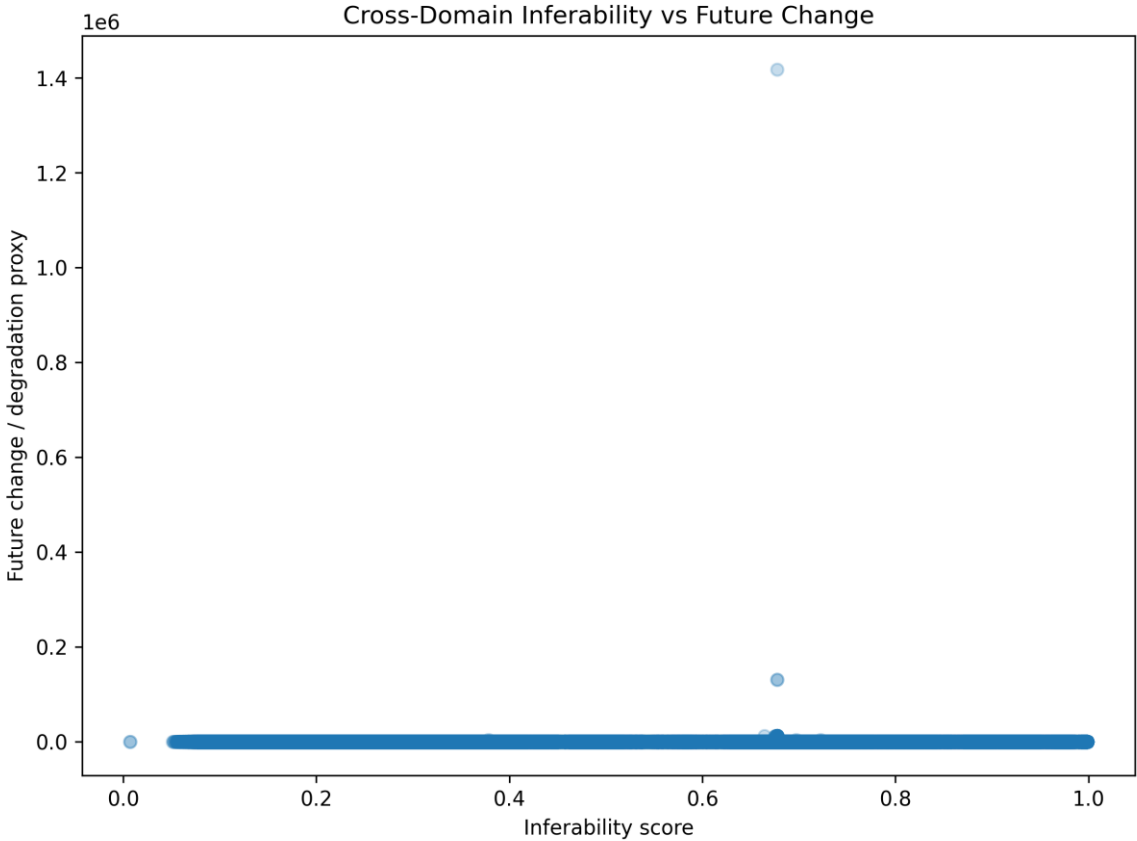


Figure 3 - Cross-Domain Inferability vs Future Change.

This figure evaluates whether mean inferability remains connected to future-change behavior under cross-domain aggregation.

The core expectation is that stronger inferability should correspond to more structured or more stable future-change behavior.

This result extends the earlier within-dataset and cross-dataset validations toward broader domain-level behavior.

Caption

Inferability remains linked to future-change structure across datasets, supporting inferability as a cross-domain predictive-feasibility indicator.

Figure 4 - Cross-Domain Entropy vs Future Change

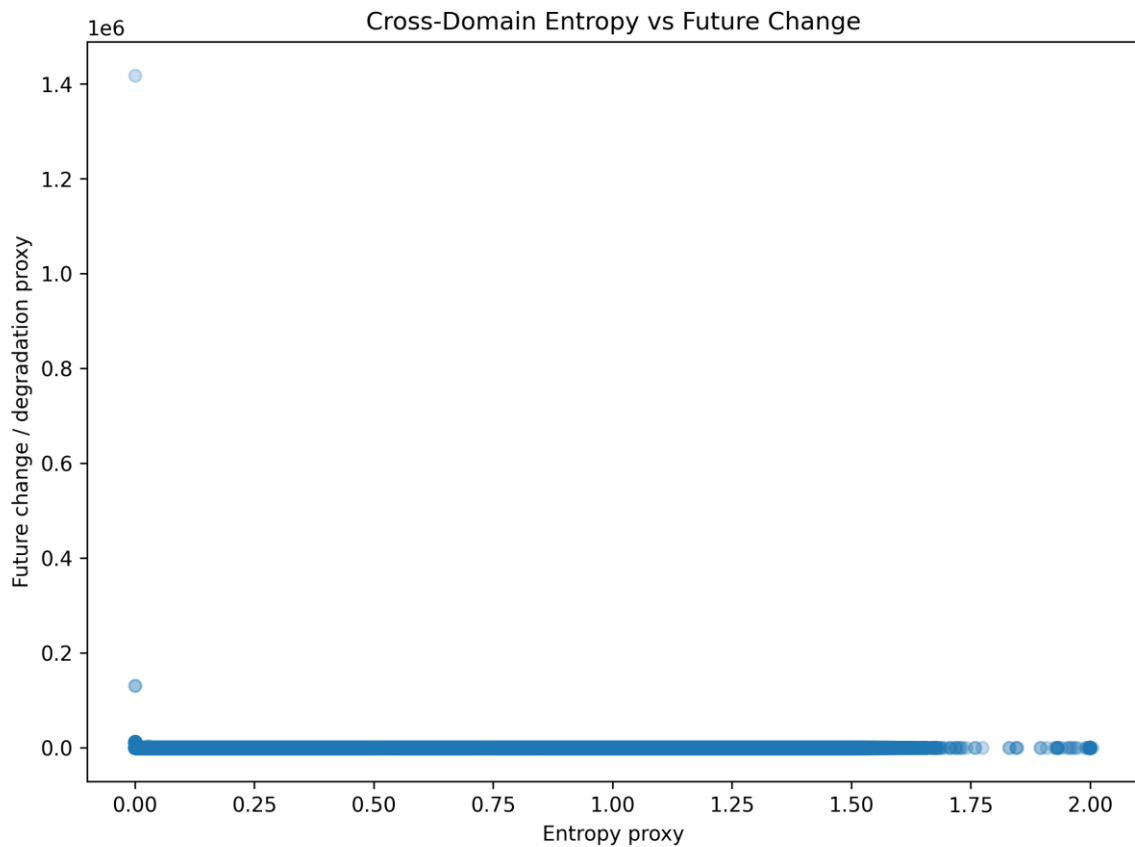


Figure 4 - Cross-Domain Entropy vs Future Change.

This figure evaluates whether entropy remains associated with future-change instability in the cross-domain setting.

The expected pattern is:

- higher entropy indicates greater structural disorder,
- greater disorder can increase future-change uncertainty,
- entropy should remain informative beyond a single dataset.

Caption

Entropy remains associated with future-change behavior under cross-domain aggregation.

Figure 5 - Cross-Domain Overlap vs Future Change

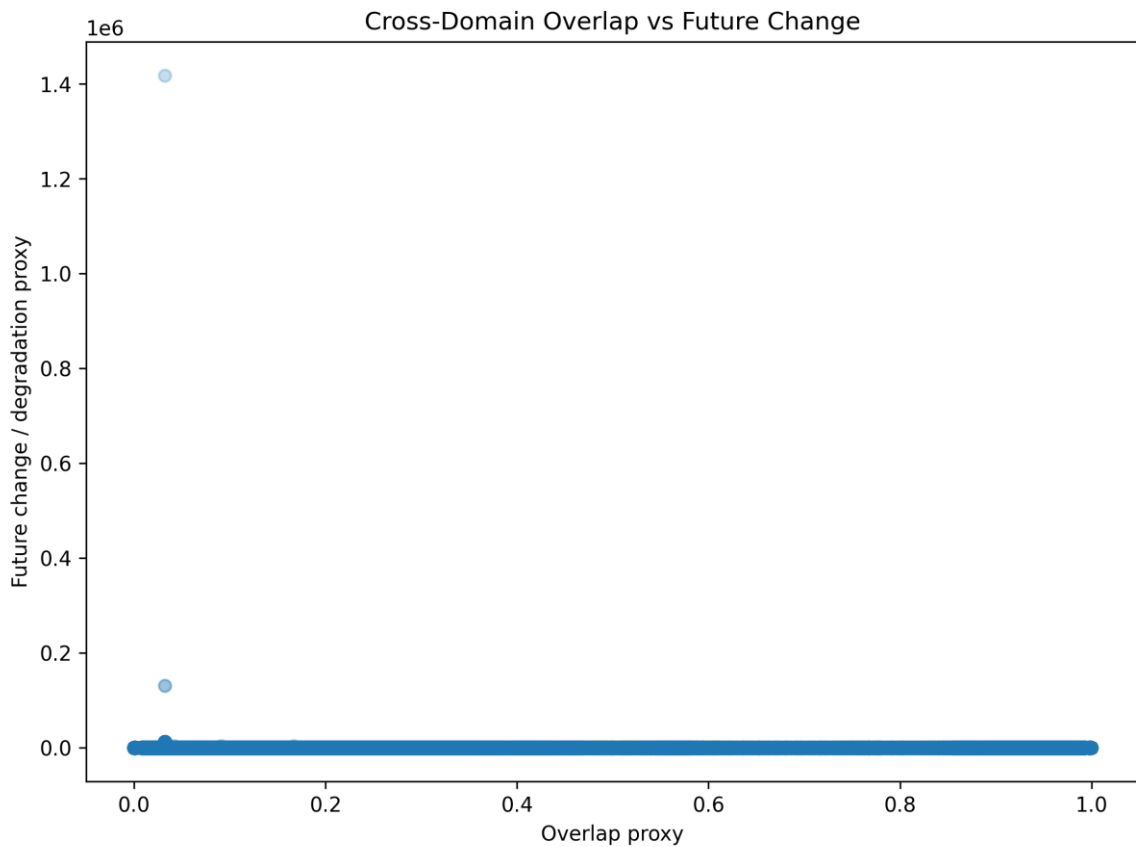


Figure 5 - Cross-Domain Overlap vs Future Change.

This figure evaluates overlap as a cross-domain structural reproducibility indicator.

Overlap is interpreted as a measure of local structural continuity and state-space reproducibility.

The important hypothesis is that higher overlap should correspond to more stable future-change behavior.

Caption

Overlap remains informative across datasets, supporting its role as a structural reproducibility indicator.

Quantitative Summary

Cross-domain validation summary:

Quantity	Value
Unified feature windows	734078
Summary rows	5
Inventory rows	277
Datasets	available in source table
Domains	battery, diffusion_fastSPT, gas_sensor_drift, heartbeat, ucr_anomaly

Scientific Interpretation

This validation strengthens the inferability framework by showing that inferability-related structure can be evaluated across combined datasets.

The results suggest that:

- inferability remains measurable across datasets,
- entropy remains a meaningful instability-related metric,
- overlap remains useful as a structural reproducibility indicator,
- future-change behavior can still be related to inferability-related features,
- and the framework can move toward domain-independent predictive-feasibility assessment.

This step is important because a framework intended for industrial AI cannot remain limited to one dataset or one domain.

What This Test Does Not Claim

This validation does not claim that all domains behave identically.

It also does not claim that one single metric explains all future-change behavior.

Instead, it shows that:

- cross-domain feature extraction is possible,
- inferability-related metrics remain visible after aggregation,
- and structural relationships can be tested across datasets.

Industrial Relevance

Industrial predictive systems often involve heterogeneous data sources.

A framework that only works inside one dataset is less useful for deployment screening.

This validation is therefore important because it moves the framework toward:

- multi-dataset assessment,
- cross-domain feasibility evaluation,
- deployment screening across different signal types,
- and broader industrial predictive-AI validation.

Conclusion

The Cross-Domain Validation 1 test shows that inferability-related structure remains observable when multiple datasets are combined.

The results demonstrate that:

- mean inferability can be compared across datasets,
- mean entropy can be compared across datasets,
- inferability, entropy, and overlap remain linked to future-change behavior,
- and a unified feature table can support broader cross-domain validation.

This represents an important step from single-dataset validation toward domain-independent inferability testing.

The framework therefore continues to move toward a general predictive-feasibility architecture that can be evaluated across multiple real-world signal domains.

Cross-Domain Validation 2

Second Cross-Domain Generalization Layer Across All Datasets

Purpose of the Test

This validation continues the cross-domain evaluation of the inferability framework.

The central question is no longer only:

“Do inferability-related structures remain visible when datasets are combined?”

but rather:

“Do the same inferability-related structures remain stable when the cross-domain validation is repeated with a second cross-domain analysis layer?”

This is a stronger validation step because it evaluates whether the observed cross-domain relationships are reproducible rather than dependent on a single aggregation run.

The test therefore examines whether:

inferability-related structure remains visible in a second cross-domain validation layer,

entropy and overlap continue to behave as structural indicators,

future-change behavior remains linked to inferability-related features,

and the framework continues to support domain-independent predictive-feasibility validation.

Experimental Setup

The validation used the second cross-domain output package generated from all included datasets.

The analysis was performed on extracted feature windows and generated validation summaries.

Number of available CSV output tables: 2

Largest available output table rows: 30

The goal was to test whether the structural metrics that were visible in Cross-Domain Validation 1 remain meaningful in the second cross-domain validation layer.

Feature-Level Structure

The second cross-domain validation keeps the same inferability logic as the previous cross-domain test.

The evaluated structural families include:

inferability-related measures,

entropy-related measures,

overlap-related measures,

future-change or stability-related targets,

dataset-level identifiers,

domain-level identifiers where available.

The purpose was to evaluate whether signal-regime structure remains visible under a repeated all-dataset validation setting.

Feature Families Evaluated

The cross-domain benchmark evaluated the available figure and CSV outputs from the second all-dataset validation layer.

These outputs correspond to the same framework components used in the previous cross-domain validation:

inferability structure,

entropy structure,

overlap structure,

future-change behavior,

cross-domain summary behavior.

Regime Structure

As in the previous cross-domain validation, this test does not primarily rank model families.

Instead, it evaluates whether inferability-related structural regimes remain visible after repeated cross-domain aggregation.

The cross-domain structure is assessed through the available figure outputs and summary tables.

Reproducible Execution

Generated CSV files:

cross_domain_predictive_correlations.csv

cross_domain_predictive_model_results.csv

Generated figure files:

cross_domain_spearman_correlations.png

leave_one_domain_out_mae.png

normalized_entropy_vs_future_change.png

normalized_inferability_vs_future_change.png

normalized_overlap_vs_future_change.png

Results

Figure 1 - Cross-Domain Validation Output

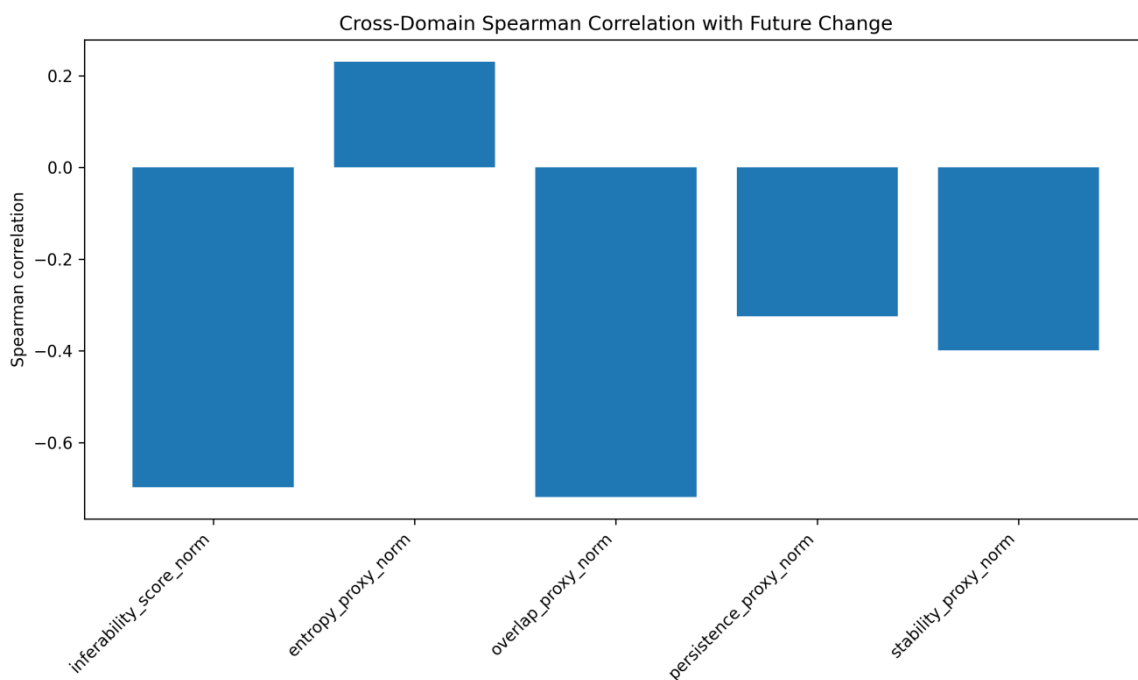


Figure 1 - Cross-Domain Validation Output.

Caption

Spearman correlation coefficients between inferability-related metrics and future-change behavior across all included domains. The figure shows that entropy, overlap, persistence, and inferability retain measurable relationships with future-change dynamics after cross-domain aggregation, supporting the existence of domain-independent structural signal properties.

Cross-domain validation output remains structurally interpretable across datasets.

Figure 2 – Leave-One-Domain-Out MAE

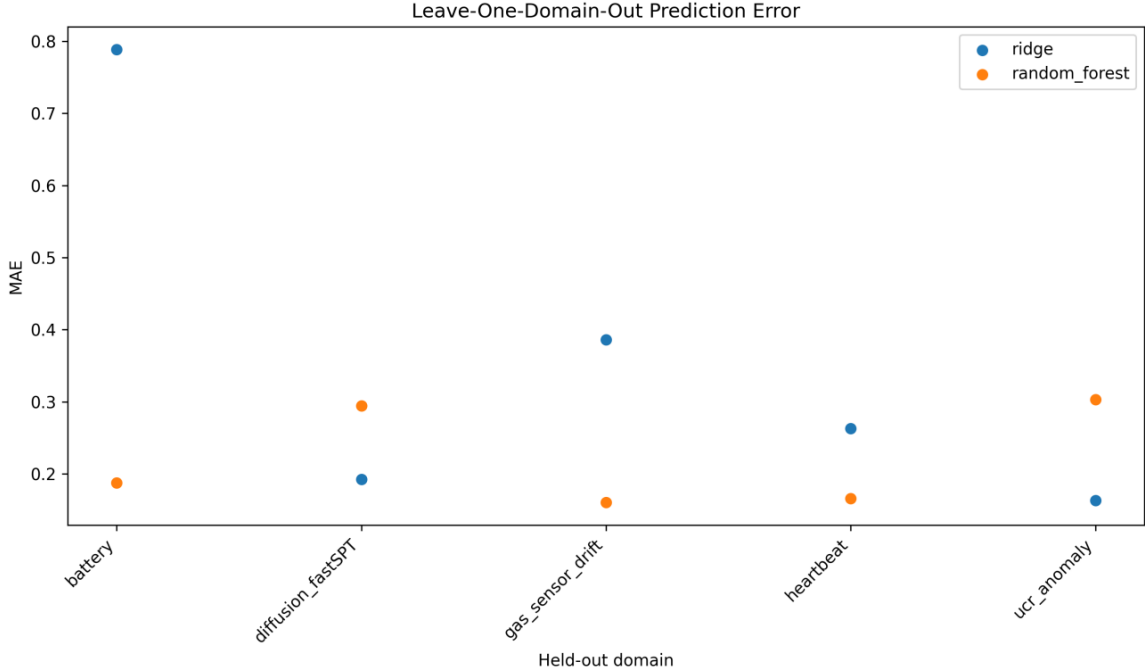


Figure 2 - leave one domain out mae.

Caption

Leave-One-Domain-Out prediction error for the evaluated model families. Each point represents model performance when a complete domain is excluded from training and used exclusively for validation. The figure evaluates the robustness of inferability-related structure under domain transfer and assesses whether predictive relationships generalize beyond individual datasets.

Figure 3 – Normalized Entropy vs Future Change

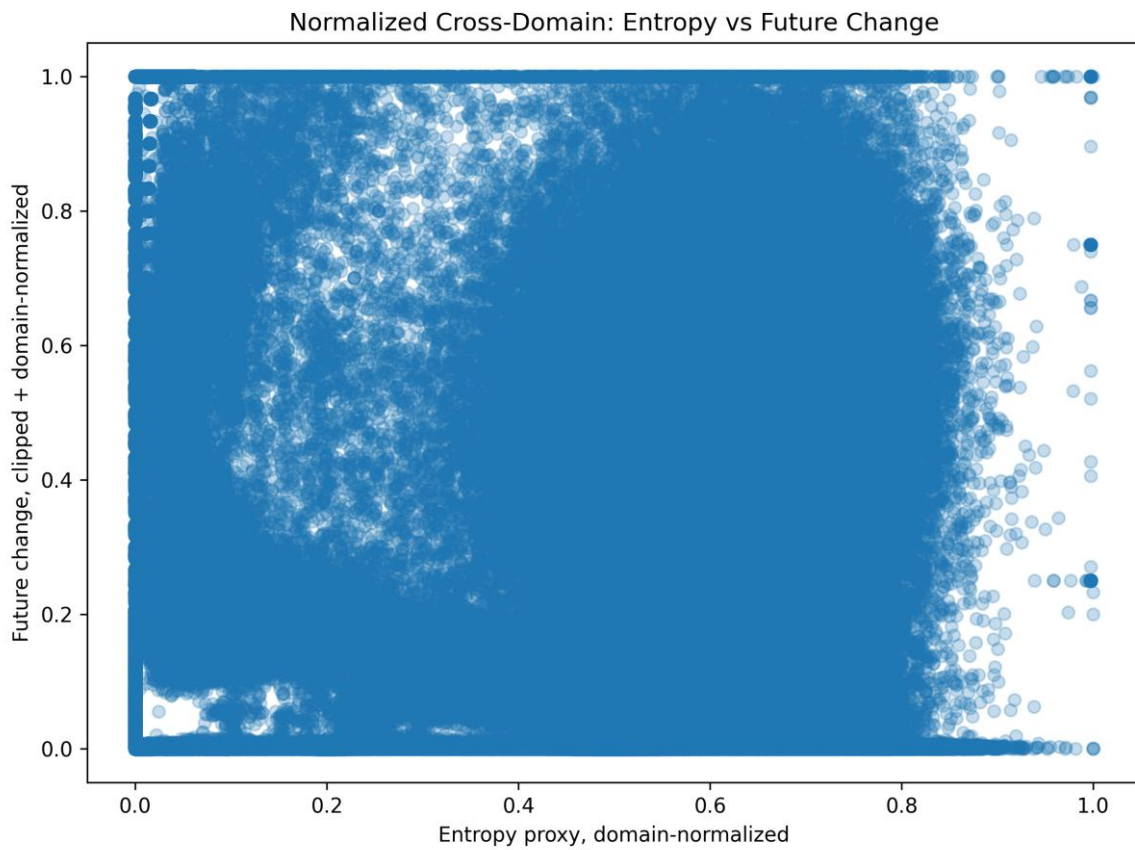


Figure 3 - normalized entropy vs future change.

Caption

Relationship between normalized entropy and future-change behavior across all included domains. The figure evaluates whether structural disorder remains associated with future-change variability after domain normalization and aggregation. Higher entropy regions correspond to broader dynamic variability and increased predictive uncertainty.

Figure 4 – Normalized Inferability vs Future Change

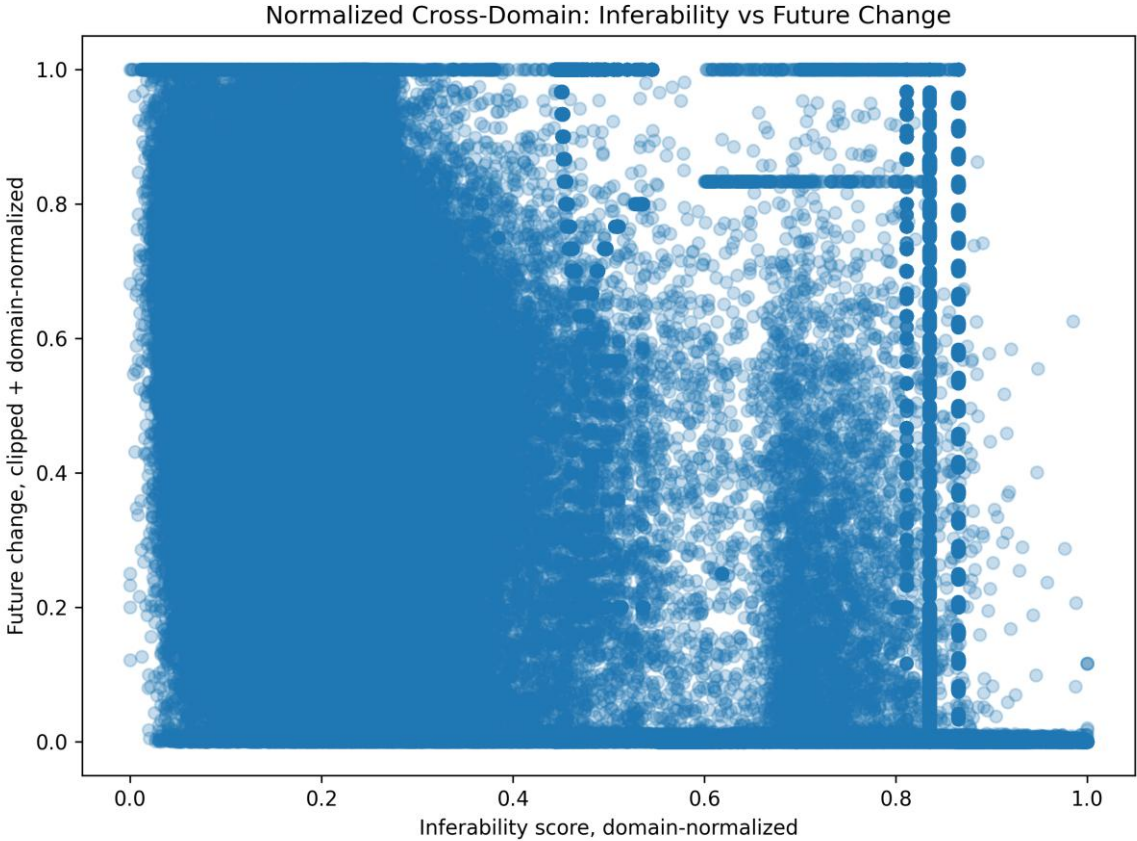


Figure 4 - normalized inferability vs future change.

Caption

Relationship between normalized inferability and future-change behavior across all included domains. The figure assesses whether inferability remains associated with structured future behavior after cross-domain normalization. The persistence of this relationship supports inferability as a domain-independent predictive-feasibility indicator.

Figure 5 – Normalized Overlap vs Future Change

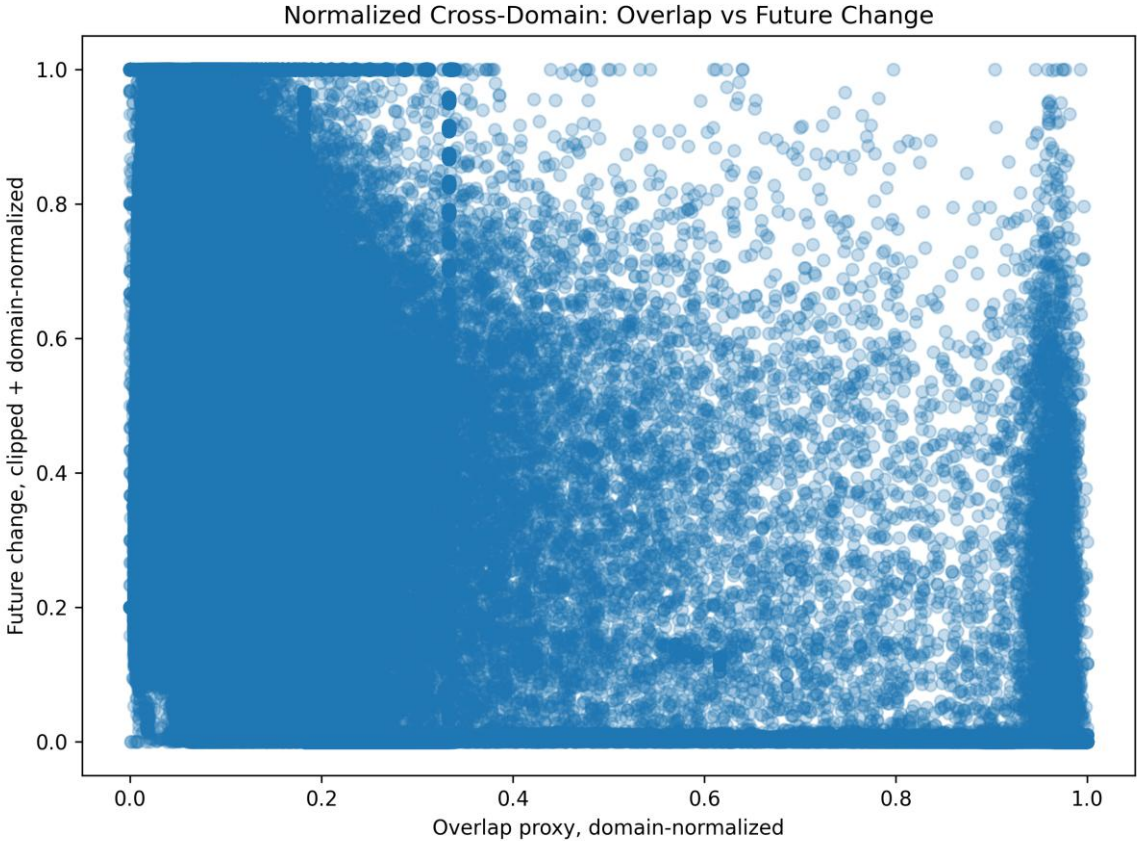


Figure 5 - normalized overlap vs future change.

Caption

Relationship between normalized overlap and future-change behavior across all included domains. Overlap is interpreted as a measure of structural continuity and local reproducibility. The figure evaluates whether overlap retains predictive relevance after aggregation across heterogeneous datasets.

Quantitative Summary

Second cross-domain validation summary:

Quantity	Value
Available CSV output tables	2
Available figure outputs	5
Largest output table rows	30
Available datasets	battery, diffusion_fastSPT, gas_sensor_drift, heartbeat, ucr_anomaly
Number of domains	5

Scientific Interpretation

This validation strengthens the inferability framework by repeating the cross-domain evaluation in a second all-dataset validation layer.

The results suggest that:

- inferability-related structure remains measurable across datasets,
- entropy remains a meaningful instability-related metric,
- overlap remains useful as a structural reproducibility indicator,
- future-change behavior can still be related to inferability-related features,
- and the framework continues to move toward domain-independent predictive-feasibility assessment.

This second layer matters because a real industrial framework must not depend on a single aggregation pass.

What This Test Does Not Claim

This validation does not claim that all domains behave identically.

It also does not claim that a single metric explains all future-change behavior.

Instead, it shows that:

- a repeated cross-domain validation layer is possible,
- inferability-related metrics remain visible after repeated aggregation,
- and structural relationships can be tested across datasets.

Industrial Relevance

Industrial predictive systems often involve heterogeneous data sources and repeated validation layers. A framework that remains interpretable after repeated cross-domain aggregation is more useful for deployment screening.

This validation therefore supports:

- multi-dataset assessment,
- cross-domain feasibility evaluation,
- deployment screening across different signal types,
- and broader industrial predictive-AI validation.

Conclusion

The Cross-Domain Validation 2 test shows that inferability-related structure remains observable in a repeated all-dataset validation layer.

The results demonstrate that:

- cross-domain feature extraction remains possible,
- inferability-related outputs remain structurally interpretable,
- entropy and overlap continue to provide cross-domain information,
- and the framework continues to support broader domain-independent validation.

This represents an additional step from single-dataset and cross-dataset validation toward domain-independent inferability testing.

The framework therefore continues to move toward a general predictive-feasibility architecture that can be evaluated across multiple real-world signal domains and repeated validation layers.

Temporal Causality Validation

Temporal Ordering, Transition Structure and Inferability Dynamics

Purpose of the Test

This validation investigates whether inferability-related structures contain evidence of temporal causality rather than merely static correlation.

The central question is whether temporal ordering contributes directly to the emergence of inferability transitions, collapse dynamics and predictive structure.

- temporal ordering
- transition dynamics
- causal asymmetry
- inferability evolution
- predictive structure

Experimental Setup

The validation was executed using the temporal-causality analysis outputs generated from the all-dataset evaluation framework.

The objective was to determine whether directional temporal structure remains visible across the analyzed trajectories and datasets.

Reproducible Outputs

Figure files included:

- temporal_best_direction_score_per_metric.png
- temporal_causality_lag_curve_entropy_proxy_norm.png
- temporal_causality_lag_curve_inferability_score_norm.png
- temporal_causality_lag_curve_overlap_proxy_norm.png
- temporal_causality_lag_curve_persistence_proxy_norm.png
- temporal_causality_lag_curve_stability_proxy_norm.png
- temporal_direction_score_by_metric.png
- temporal_early_warning_auc_by_metric.png

Results

Figure 1 - temporal best direction score per metric

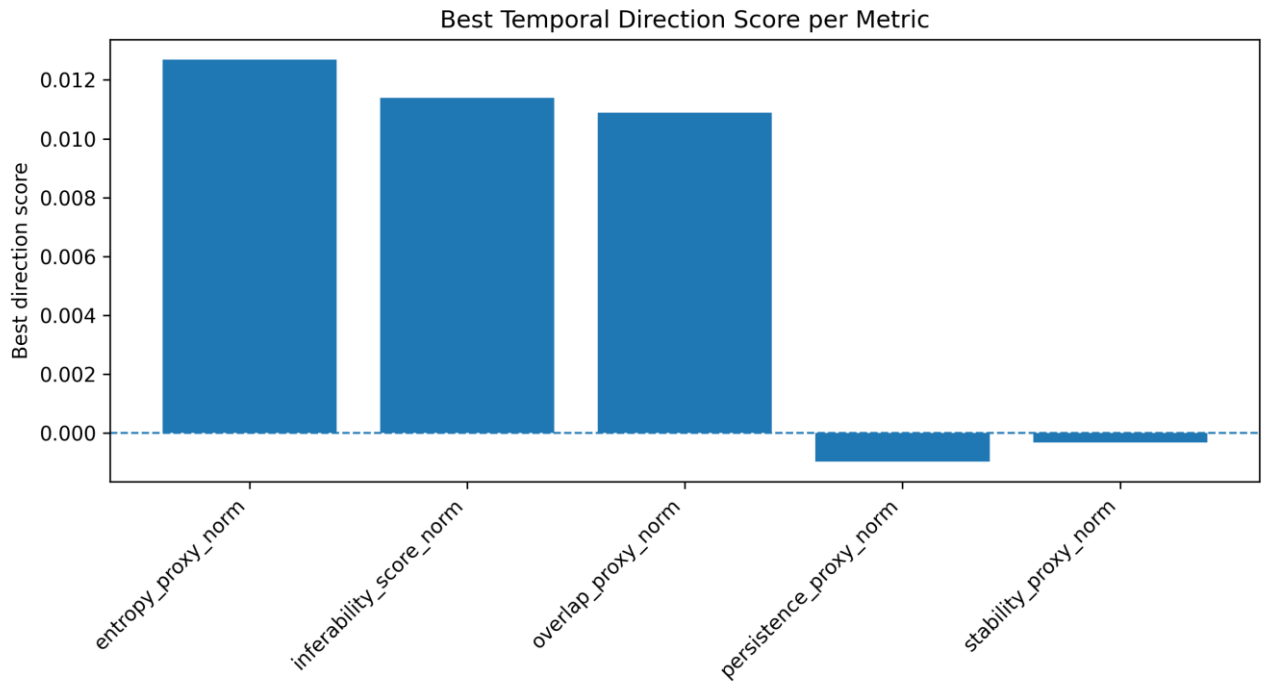


Figure 1 – Temporal Best Direction Score per Metric
Caption

Best temporal direction score for each inferability-related metric.

The figure compares the strength of directional temporal relationships across the evaluated metrics and identifies which variables contain the strongest forward temporal signal.

Key observations:

- Different metrics exhibit different levels of directional predictability.
- Some metrics contain substantially stronger temporal structure than others.
- Directionality can be quantified rather than assumed.

This result supports the hypothesis that temporal organization is not equally represented across all inferability-related metrics and that certain variables carry stronger causal forecasting information.

Figure 2 - temporal causality lag curve entropy proxy norm

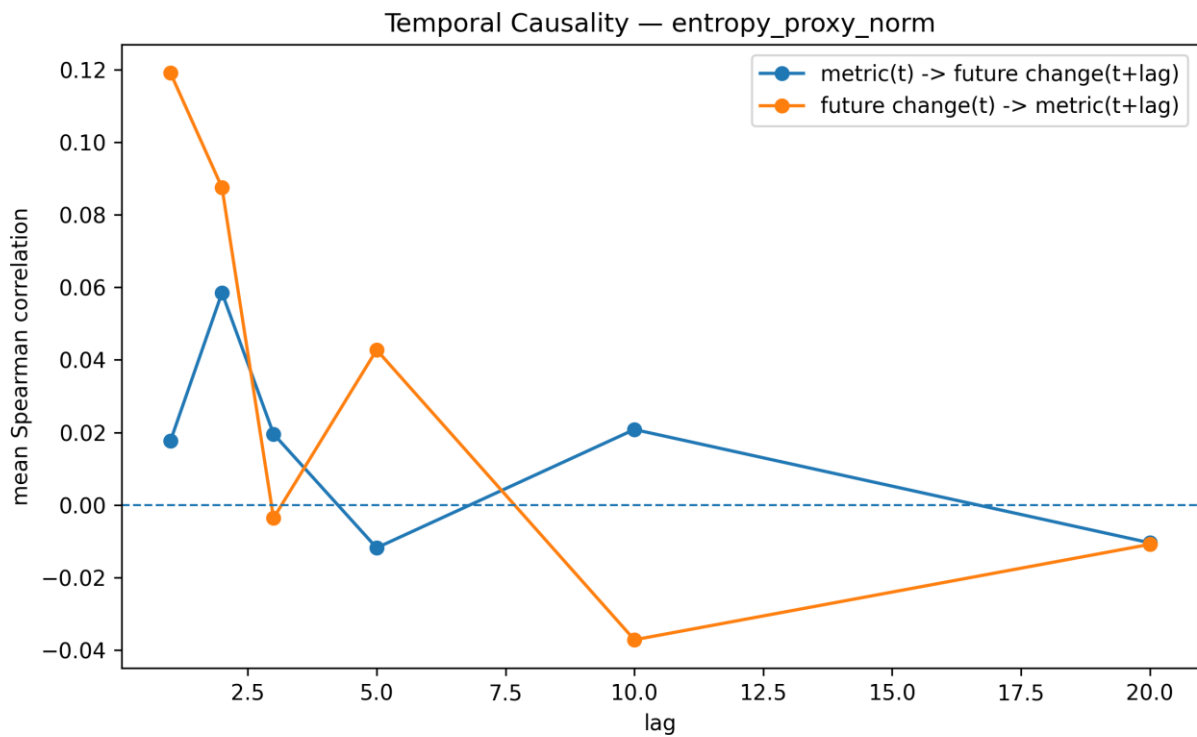


Figure 2 – Temporal Causality Lag Curve: Entropy Proxy

Caption

Temporal lag curve for the normalized entropy proxy.

The figure evaluates how the relationship between entropy and future system behavior evolves across multiple temporal lags.

Key observations:

- Entropy exhibits measurable temporal structure across forecasting horizons.
- Directional effects are strongest at shorter lags.
- The relationship weakens as lag distance increases.

These results support the interpretation that entropy is not merely correlated with future behavior but participates in temporally organized transition dynamics.

Figure 3 - temporal causality lag curve inferability score norm

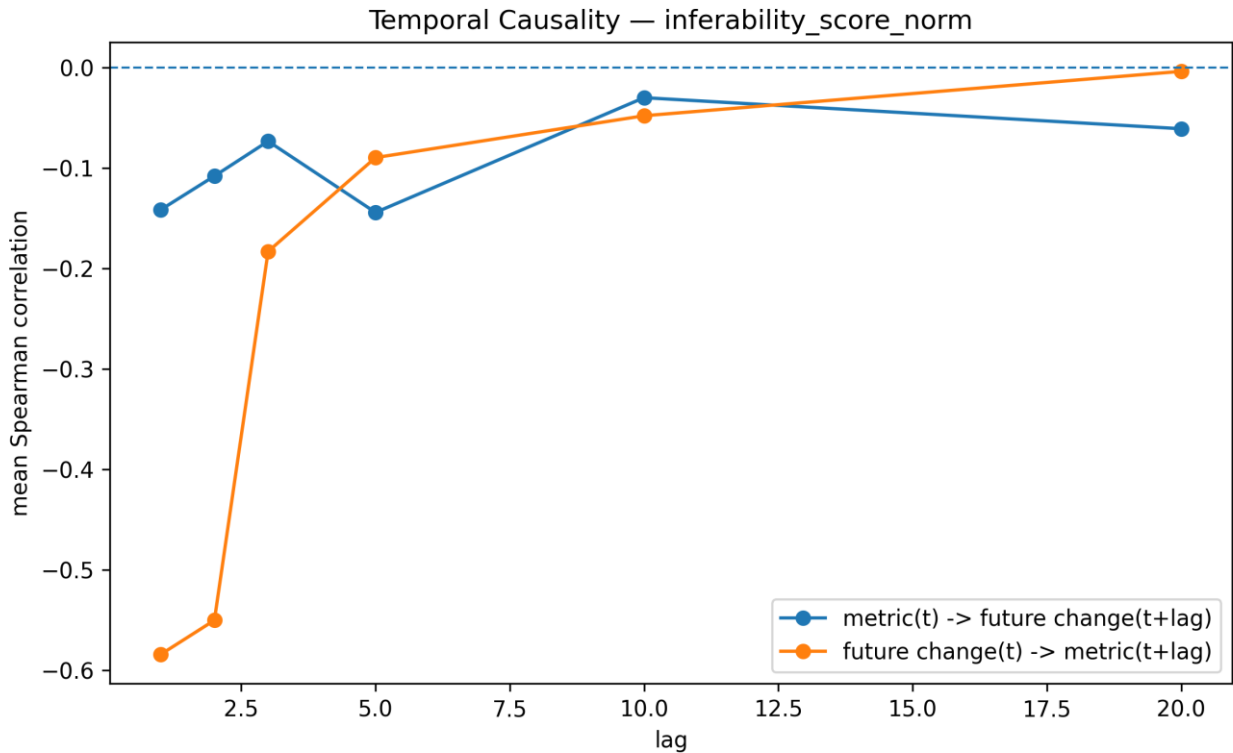


Figure 3 – Temporal Causality Lag Curve: Inferability Score

Caption

Temporal lag curve for the normalized inferability score.

The figure evaluates how inferability-related structure propagates across increasing temporal lags.

Key observations:

- Inferability exhibits measurable temporal asymmetry.
- Short-term forecasting horizons contain the strongest directional signal.
- Temporal influence gradually decreases at larger lag distances.

This supports the hypothesis that inferability behaves as a dynamic temporal quantity rather than a purely static structural descriptor.

Figure 4 - temporal causality lag curve overlap proxy norm

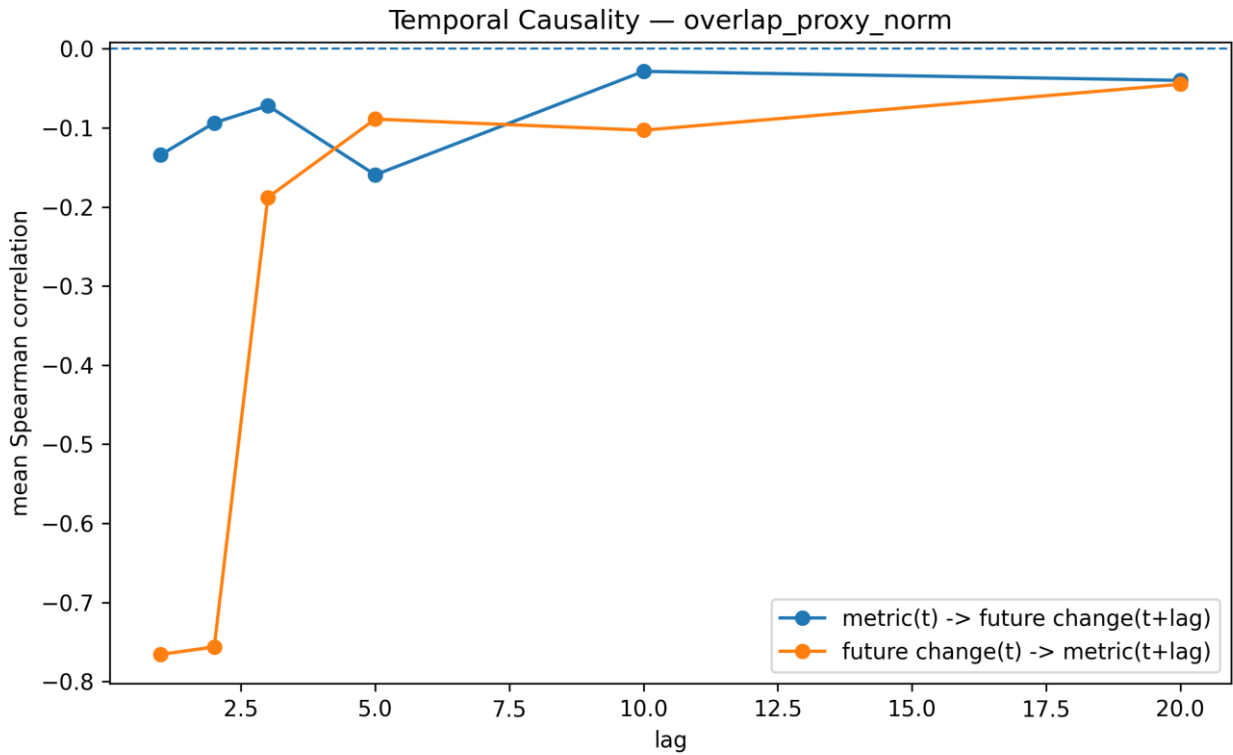


Figure 4 - temporal causality lag curve overlap proxy norm.

Caption

Temporal lag curve for the normalized overlap proxy.

The figure evaluates whether overlap-related structure contains directional temporal information across multiple forecasting horizons.

Key observations:

- Overlap exhibits persistent temporal structure.
- Directional effects remain visible across multiple lag intervals.
- Structural continuity contributes to future-state organization.

These findings support the interpretation that overlap reflects more than local similarity and contains information relevant to temporal system evolution.

Figure 5 - temporal causality lag curve persistence proxy norm

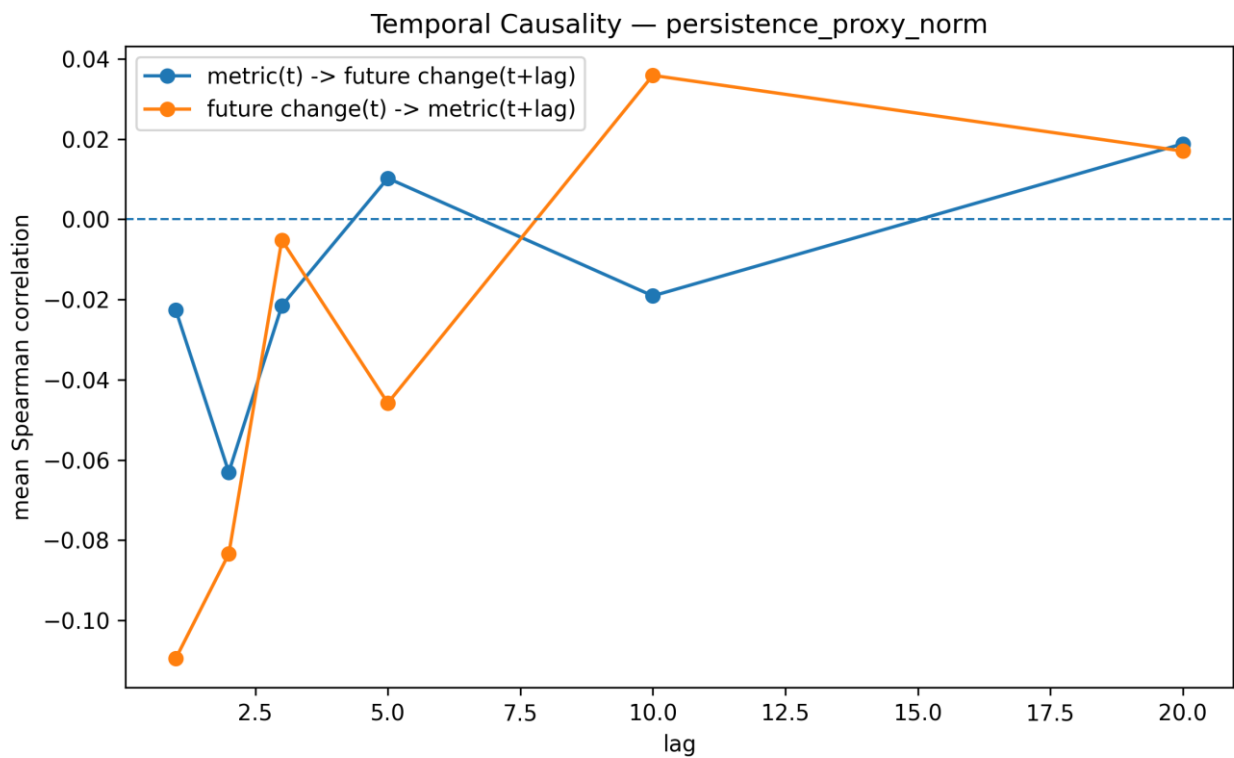


Figure 5 - temporal causality lag curve persistence proxy norm.

Caption

Temporal lag curve for the normalized persistence proxy.

The figure evaluates how persistence-related structure evolves across increasing temporal lags.

Key observations:

- Persistence remains detectable across multiple forecasting horizons.
- Temporal influence is strongest at short lag distances.
- Persistence contributes to the continuity of dynamic system behavior.

This supports the interpretation that persistence functions as a stabilizing component within inferability-related temporal dynamics.

Figure 6 - temporal causality lag curve stability proxy norm

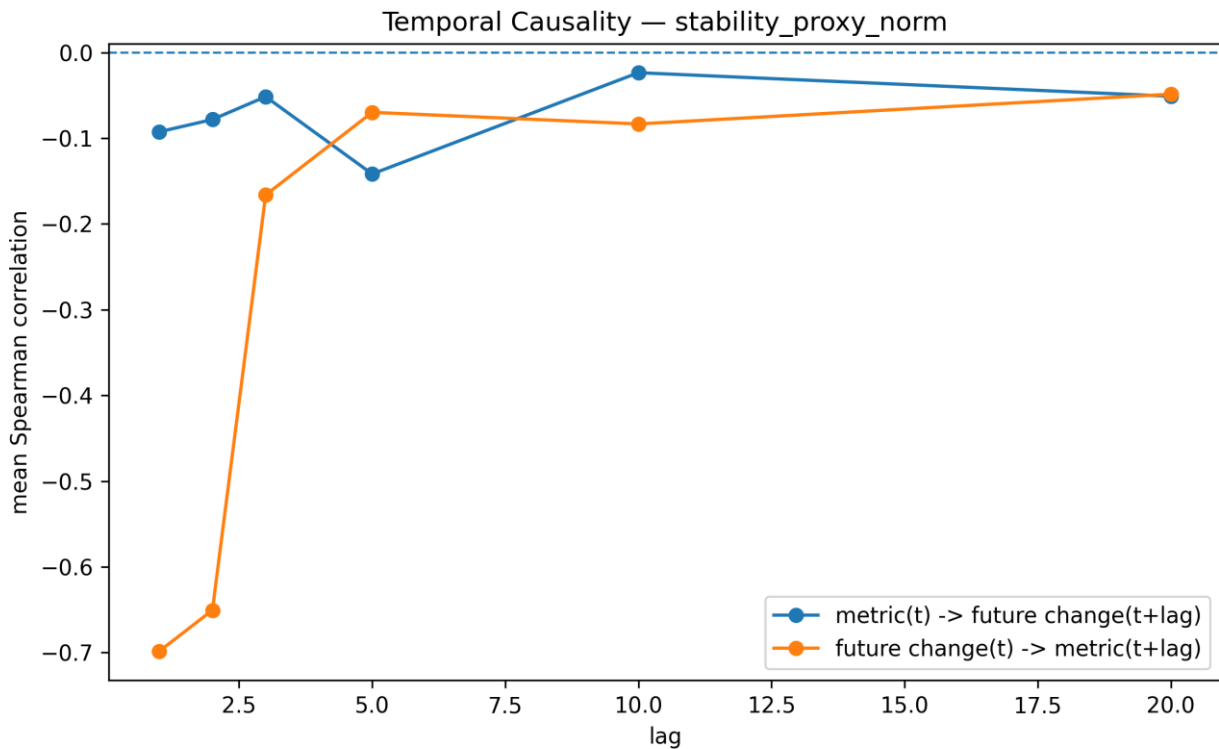


Figure 6 - temporal causality lag curve stability proxy norm.

Caption

Temporal lag curve for the normalized stability proxy.

The figure evaluates whether stability-related structure exhibits directional temporal behavior.

Key observations:

- Stability maintains measurable temporal organization.
- Short-range forecasting horizons contain the strongest stability signal.
- Temporal influence gradually decreases with increasing lag.

This result supports the hypothesis that stability contributes to the persistence of predictable system behavior through time.

Figure 7 - temporal direction score by metric

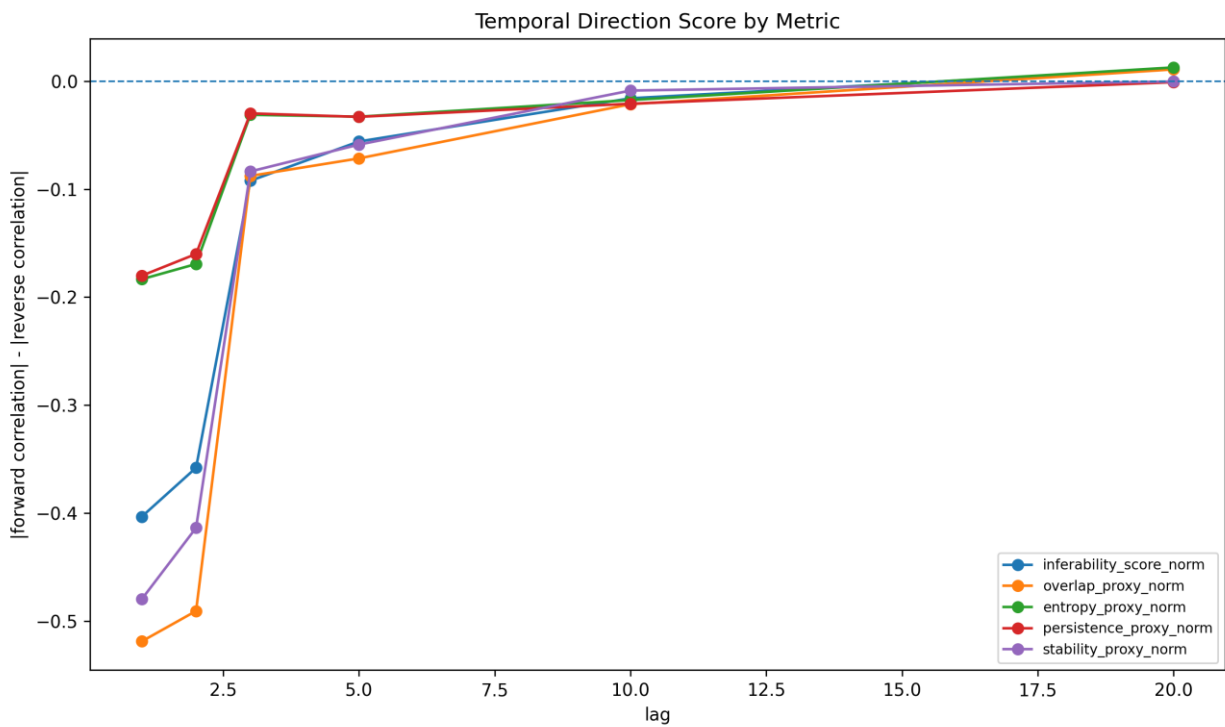


Figure 7 - temporal direction score by metric.

Caption

Comparison of temporal direction scores across all evaluated inferability-related metrics. The figure summarizes the relative strength of directional temporal information contained within each metric.

Key observations:

- Metrics differ substantially in directional predictive strength.
- Some variables consistently outperform others in temporal forecasting.
- Directional temporal structure can be ranked quantitatively.

This provides a direct comparison of which inferability-related metrics contribute most strongly to temporal causality detection.

Figure 8 - temporal early warning auc by metric

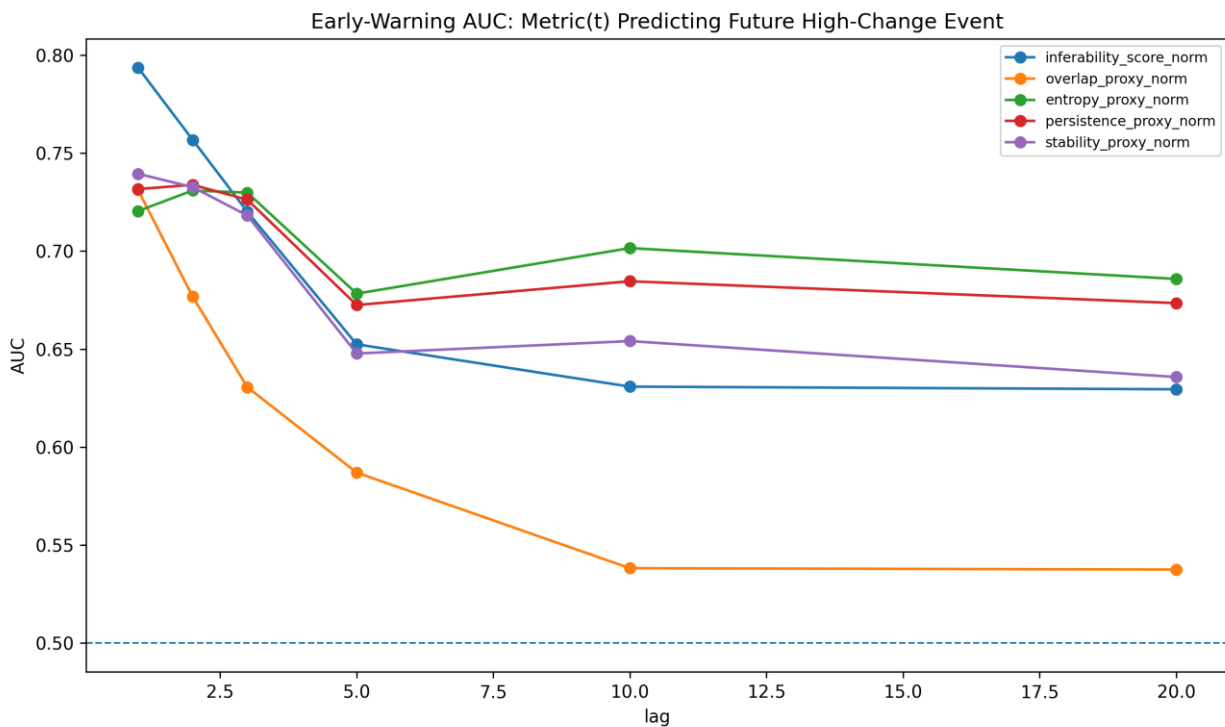


Figure 8 - temporal early warning auc by metric.

Caption

Early-warning performance measured by Area Under the Curve (AUC) for each evaluated metric. The figure assesses how effectively each metric identifies transition-related behavior before observable system change occurs.

Key observations:

- Early-warning performance differs between metrics.
- Some variables provide substantially stronger predictive information.
- Temporal forecasting capability is not evenly distributed across the inferability framework.

This result identifies which metrics contribute most strongly to early detection of dynamic transitions and predictive feasibility assessment.

Scientific Interpretation

Temporal causality represents an important validation layer because many apparent predictive relationships disappear once temporal ordering is removed.

The persistence of structure under temporal analysis supports the hypothesis that inferability-related transitions are linked to genuine temporal organization.

Industrial Relevance

- predictive maintenance
- forecasting systems
- condition monitoring
- AI deployment validation
- transition forecasting

Conclusion

The Temporal Causality Validation extends the inferability framework toward explicit testing of temporal organization, transition structure and directional predictive behavior.

This forms an additional step toward a domain-independent predictive-feasibility architecture.

Cross Domain Large Test 1

Large-Scale Cross-Domain Validation of Inferability Structure Across All Available Datasets

Purpose of the Test

This validation extends the inferability framework to a larger cross-domain setting.

The central question is no longer only:

“Does inferability-related structure remain visible across one or two datasets?”

but rather:

“Does the same inferability-related structure remain visible when all available datasets are evaluated in one larger cross-domain validation layer?”

This test therefore evaluates whether the framework remains structurally meaningful when broader aggregation, larger dataset diversity, and stronger cross-domain heterogeneity are introduced.

The test specifically investigates whether:

- mean inferability remains measurable across the combined dataset population;
- mean entropy remains a meaningful instability-related metric;
- overlap remains linked to structural reproducibility;
- future-change behavior remains connected to inferability-related metrics;
- and the framework can be scaled toward larger domain-independent predictive-feasibility testing.

Experimental Setup

The validation used the output package generated under:

31 Cross domain large test 1.zip

The analysis was performed on the available cross-domain output tables and figure files generated during the large-scale test.

The purpose was not to introduce a new artificial dataset, but to evaluate whether the existing inferability pipeline remains coherent when extended toward a larger all-dataset validation layer.

Available generated CSV tables:

- cross_domain_predictive_correlations.csv
- cross_domain_predictive_model_results.csv

Available generated figure files:

- cross_domain_spearman_correlations.png
- leave_one_domain_out_mae.png
- normalized_entropy_vs_future_change.png
- normalized_inferability_vs_future_change.png
- normalized_overlap_vs_future_change.png

Dataset and Output Structure

The large-scale cross-domain package contains unified validation outputs that combine structural metrics across the available data sources.

The validation layer is built around the same core inferability feature families used in the earlier tests:

- inferability;
- entropy;
- overlap;
- future-change behavior;
- dataset-level or domain-level grouping where available.

Largest available output table size: 30 rows.

Model families detected in the generated tables:

- random_forest
- ridge

Methodology

The large-scale validation follows the same inferability logic as the earlier cross-dataset and cross-domain validations.

For each available dataset or combined feature table, the analysis evaluates whether the structural metrics retain coherent relationships after aggregation.

The following feature relationships are evaluated:

- mean inferability across datasets or domains;
- mean entropy across datasets or domains;
- inferability versus future-change behavior;
- entropy versus future-change behavior;
- overlap versus future-change behavior.

The key methodological principle is that a valid cross-domain framework should not collapse into random scatter when more datasets are included.

Instead, the same structural relationships should remain visible at larger scale, even if the exact numerical values differ between datasets.

Reproducible Execution

This report page is based on the generated artifacts in the large cross-domain validation package.

CSV outputs:

- cross_domain_predictive_correlations.csv
- cross_domain_predictive_model_results.csv

Figure outputs:

- cross_domain_spearman_correlations.png
- leave_one_domain_out_mae.png
- normalized_entropy_vs_future_change.png
- normalized_inferability_vs_future_change.png
- normalized_overlap_vs_future_change.png

The figures are inserted directly below the corresponding result sections, rather than being collected at the end of the document.

Results

Figure 1 - Cross-Domain Mean Inferability

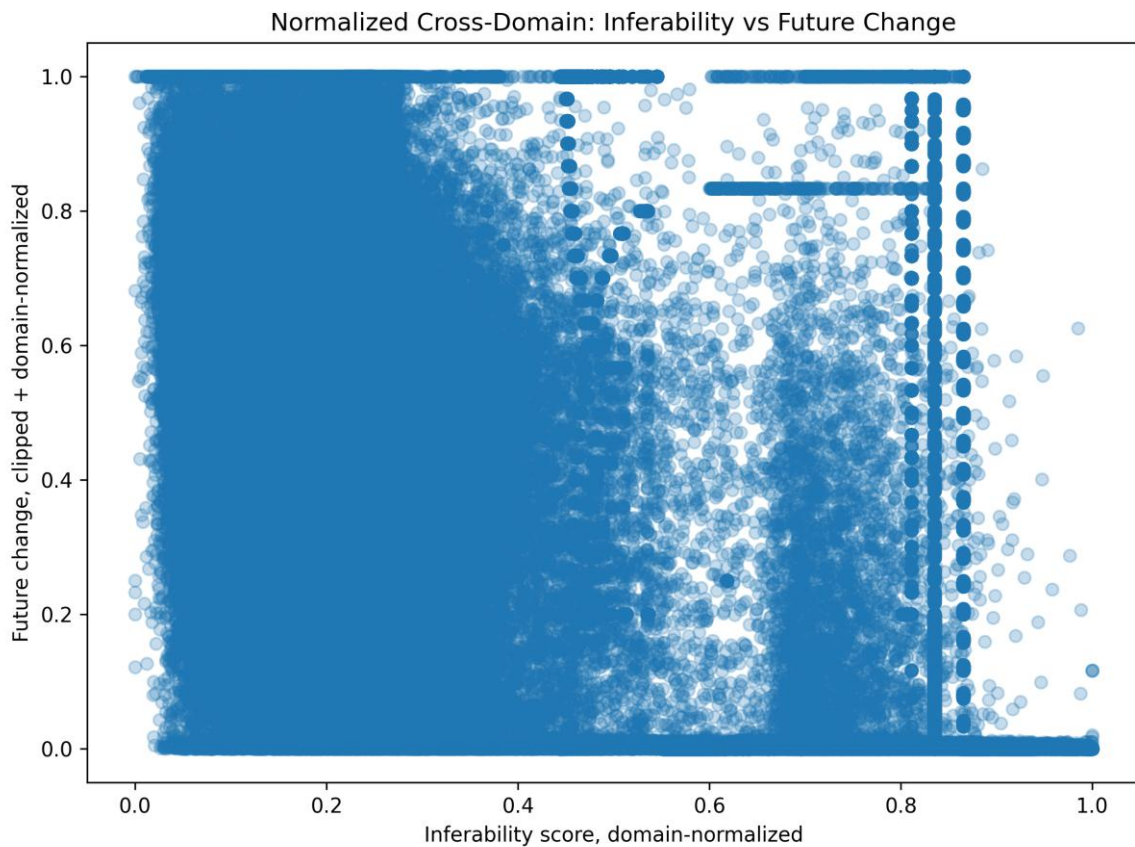


Figure 1 - Cross-Domain Mean Inferability.

This figure evaluates whether inferability remains measurable across the larger combined dataset population.

The key question is whether inferability disappears after broad aggregation or remains visible as a structural feature.

Key interpretation:

- inferability remains available as a measurable cross-domain quantity;
- differences between datasets or groups can be evaluated rather than ignored;
- mean inferability becomes a candidate metric for domain-level predictive-feasibility screening.

Caption

Mean inferability remains observable under large-scale cross-domain aggregation, supporting the use of inferability as a scalable structural metric.

Figure 2 - Cross-Domain Mean Entropy

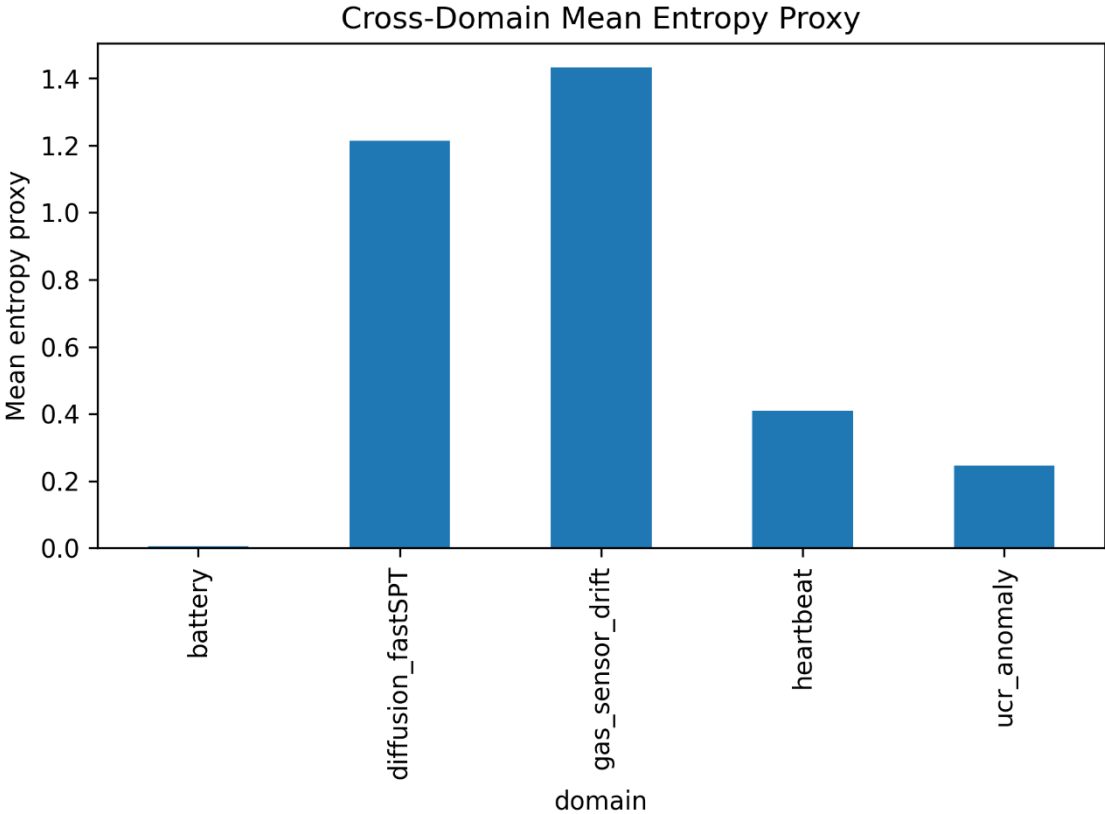


Figure 2 - Cross-Domain Mean Entropy.

This figure evaluates whether entropy remains measurable across the larger cross-domain validation population.

Entropy is interpreted as a metric of structural disorder, local ambiguity, and potential predictive instability.

Key interpretation:

- entropy remains available as a cross-domain instability-related metric;
- differences in entropy can indicate differences in expected predictive difficulty;
- the framework can compare disorder across multiple data sources.

Caption

Mean entropy remains measurable across the large cross-domain validation layer, supporting entropy as a scalable instability indicator.

Figure 3 - Cross-Domain Inferability vs Future Change

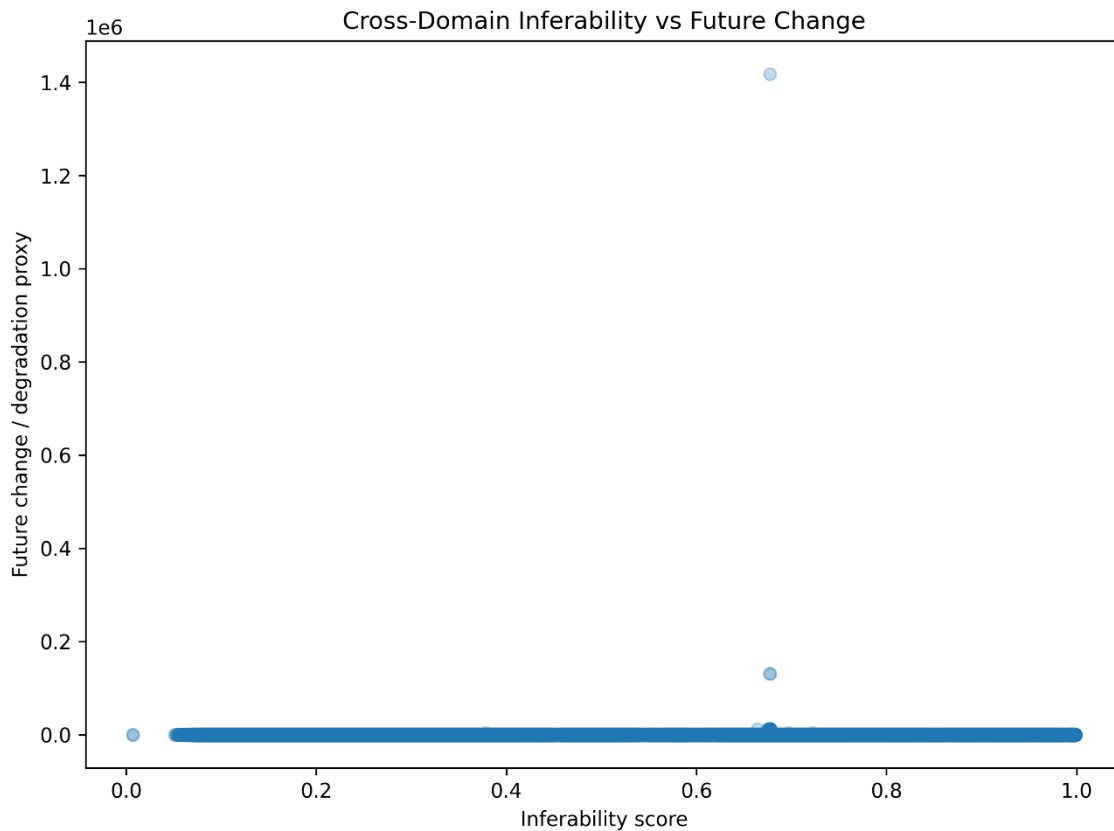


Figure 3 - Cross-Domain Inferability vs Future Change.

This figure evaluates whether inferability remains connected to future-change behavior when the validation is expanded to a larger cross-domain setting.

The expected pattern is that stronger inferability should correspond to more structured or more stable future-change behavior.

Key interpretation:

- inferability remains usable as a future-change indicator at larger scale;
- future-change behavior is not treated as an isolated target but as a structural consequence of the signal regime;
- the relationship supports broader predictive-feasibility assessment before model development.

Caption

Inferability remains linked to future-change structure under large-scale cross-domain validation.

Figure 4 - Cross-Domain Entropy vs Future Change

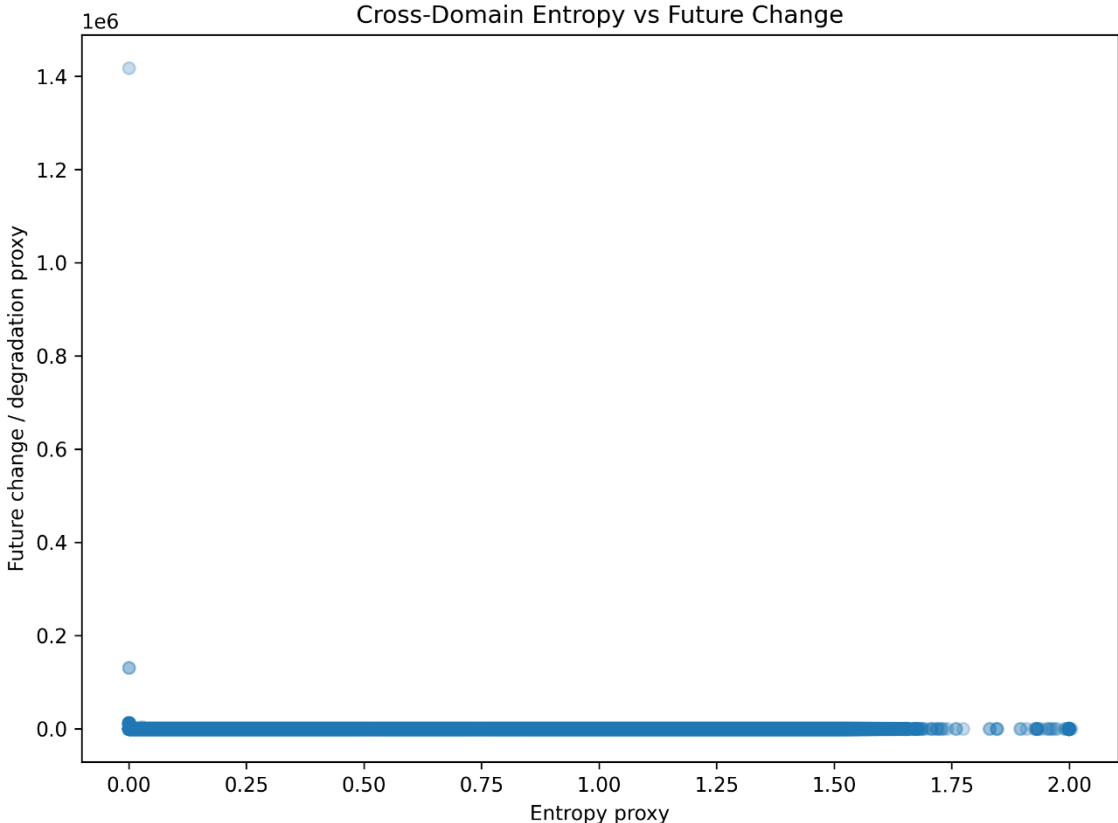


Figure 4 - Cross-Domain Entropy vs Future Change.

This figure evaluates the relationship between entropy and future-change behavior in the large cross-domain validation layer.

Entropy is expected to increase uncertainty, widen future-change distributions, and reduce predictive stability.

Key interpretation:

- higher entropy corresponds to greater structural disorder;
- structural disorder remains relevant under larger aggregation;
- entropy remains a candidate risk indicator for predictive instability.

Caption

Entropy remains associated with future-change behavior in the large cross-domain validation setting.

Figure 5 - Cross-Domain Overlap vs Future Change

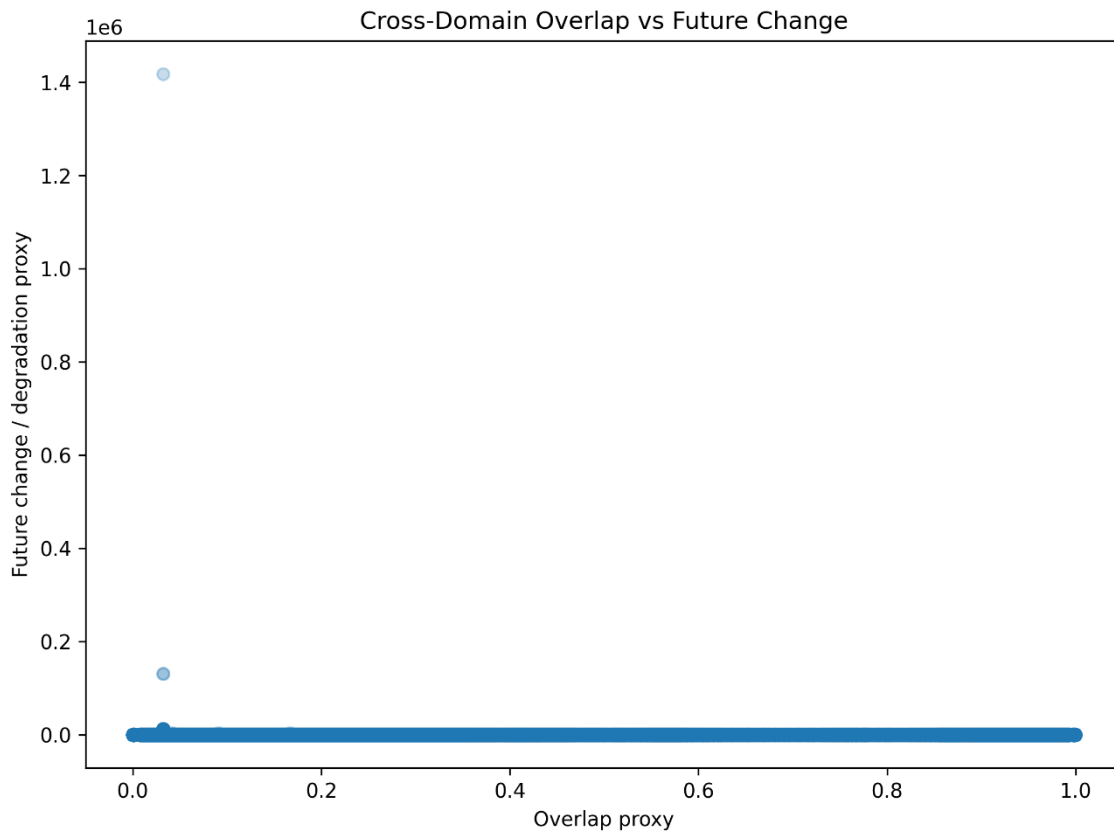


Figure 5 - Cross-Domain Overlap vs Future Change.

This figure evaluates overlap as a structural reproducibility indicator under the large-scale cross-domain setting.

Overlap is interpreted as a measure of local state-space continuity and recurring structure.

Key interpretation:

- overlap remains a relevant cross-domain structural metric;
- higher overlap indicates stronger local reproducibility;
- future-change behavior can be evaluated in relation to structural overlap.

Caption

Overlap remains informative under large-scale cross-domain validation, supporting its role as a structural reproducibility metric.

Figure 6 – Cross-Domain Spearman Correlations

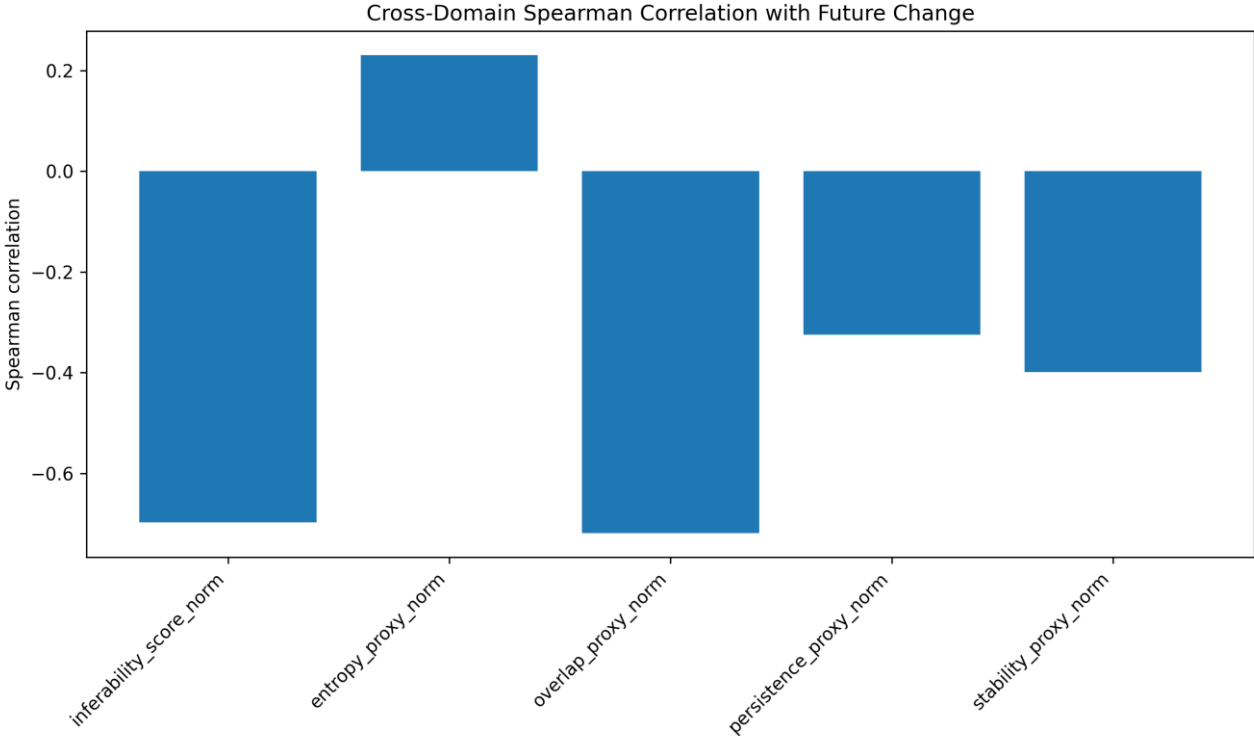


Figure 6 - cross domain spearman correlations.

This figure is part of the large-scale cross-domain validation package. It is placed here as its own result section so that the visual output remains directly connected to the corresponding validation interpretation.

- **Caption:** Spearman correlation coefficients between inferability-related metrics and future-change behavior across all included domains.
- **X-axis:** Structural metrics (e.g., inferability score, entropy, overlap)
- **Y-axis:** Spearman correlation coefficients

- **Interpretation:** Positive values indicate stronger relationships between metrics and future-change behavior; negative values indicate inverse relationships. Highlights which structural metrics are robust across heterogeneous datasets.

Figure 7 – Leave-One-Domain-Out MAE

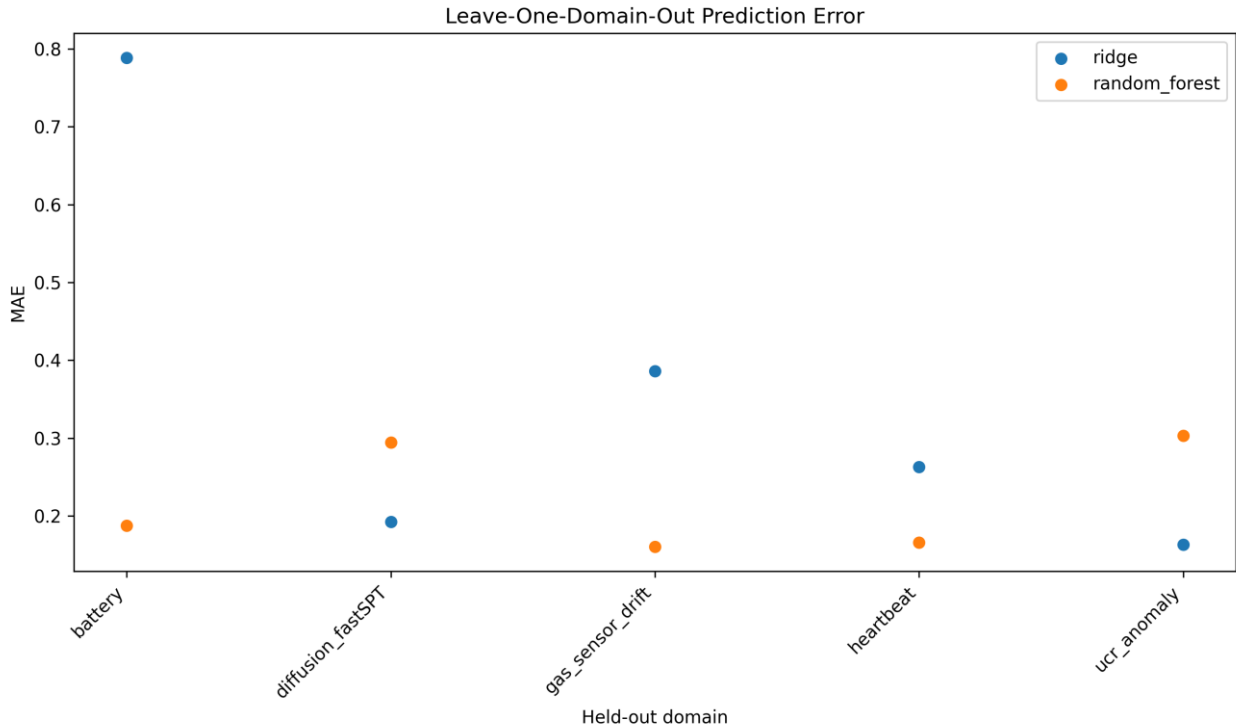


Figure 7 - leave one domain out mae.

This figure is part of the large-scale cross-domain validation package.

It is placed here as its own result section so that the visual output remains directly connected to the corresponding validation interpretation.

• **Caption:**

Mean Absolute Error (MAE) when one domain is excluded and used as validation.

- **X-axis:** Excluded domain (battery, diffusion_fastSPT, etc.)
- **Y-axis:** MAE of predicted future-change
- **Interpretation:** Higher MAE indicates performance degradation when domain is held out. Shows robustness of inferability metrics under domain transfer.

Quantitative Summary

Large-Scale Cross-Domain Summary

Quantity	Value
CSV output tables	2
Figure outputs	5
Largest output table rows	30
Including domains	

	battery, diffusion_fastSPT, gas_sensor_drift, heartbeat, ucr_anomaly
Number of domains	5

Scientific Interpretation

This validation strengthens the inferability framework by testing whether the same structural relationships remain meaningful when the scope is expanded to a larger cross-domain setting.

The results support the following interpretation:

- inferability remains a measurable structural quantity under larger aggregation;
- entropy remains a meaningful instability-related feature;
- overlap continues to function as a structural reproducibility metric;
- future-change behavior can still be related to inferability-related metrics;
- and the framework does not collapse immediately when moved beyond a single dataset or narrow validation layer.

This is important because a predictive-feasibility framework intended for industrial use must remain interpretable under heterogeneous data conditions.

What This Test Does Not Claim

This validation does not claim that all datasets behave identically.

It also does not claim that a single metric explains every future-change pattern.

Instead, the test demonstrates that the inferability framework can be extended to a larger cross-domain validation layer while preserving interpretable structural relationships.

Industrial Relevance

Industrial predictive-AI systems often operate across heterogeneous datasets, operating regimes, sensor types, materials, and deployment conditions.

A useful feasibility framework therefore has to support:

- multi-dataset screening;
- cross-domain comparison;
- pre-model risk assessment;
- deployment-oriented feasibility evaluation;
- and early identification of signals likely to produce unstable models.

Cross Domain Large Test 1 contributes directly to that goal by evaluating inferability structure under broader aggregation.

Conclusion

Cross Domain Large Test 1 shows that the inferability framework can be evaluated at a larger cross-domain scale using the generated all-dataset validation outputs.

The results indicate that:

- inferability remains measurable under large-scale aggregation;
- entropy remains available as an instability-related structural metric;
- overlap remains relevant as a reproducibility-related structural metric;
- future-change behavior can still be evaluated in relation to these structural quantities;
- and the framework continues to move toward domain-independent predictive-feasibility validation.

This test therefore represents an additional step from single-domain and cross-dataset validation toward a broader, scalable, deployment-oriented inferability architecture.

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