TDW-XDrift: When Does Decay-Weighted Explainability Help?

A Systematic Analysis of Temporal SHAP Attribution for Concept Drift Root-Cause Localization

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Abstract

Concept drift detection is critical for maintaining the reliability of streaming classifiers, yet explainable drift detection methods typically attribute root causes using static, uniformly weighted SHAP windows and rarely examine whether temporal weighting schemes are actually beneficial for this task. This paper presents a systematic empirical analysis of Temporal Decay-Weighted SHAP (TDW-SHAP) attribution for root-cause localization of concept drift in streaming classification. We evaluate three base drift detectors (ADWIN, DDM, KSWIN) combined with two explainability configurations (uniform-weighted standard SHAP and exponentially decay-weighted TDW-SHAP across four decay rates, lambda in {0.001, 0.01, 0.05, 0.1}) under three synthetically injected drift regimes (sudden, gradual, recurring) on the Electricity (Elec2) benchmark dataset, restricting drift injection to features with above-median baseline importance to guarantee theoretically detectable ground truth. Across 456 matched detector-explainability observations, standard (uniform-weighted) SHAP significantly outperforms TDW-SHAP in root-cause attribution accuracy overall (41.2 percent vs. 32.7 percent, paired t-test t = -5.42, p < 0.0001). Critically, this degradation follows a clear dose-response pattern: light decay (lambda <= 0.01) is statistically indistinguishable from the uniform-weighted baseline, while aggressive decay (lambda >= 0.05) produces a consistent, monotonic decline in attribution accuracy across sudden and recurring drift. Gradual drift is comparatively insensitive to decay weighting at low lambda. These results indicate that decay-based forgetting mechanisms, while established as beneficial for drift detection latency, are misaligned with the contrastive, pre- and post-drift information requirements of root-cause localization, and that the appropriateness of temporal weighting for explainable drift analysis is decay-rate- and drift-type-dependent rather than universally beneficial.

Keywords—*concept drift, explainable AI, SHAP, temporal decay weighting, root-cause analysis, streaming classification*

1. Introduction

Streaming classification systems deployed in non-stationary environments are vulnerable to concept drift: changes in the underlying joint distribution P(X, y) that degrade the predictive validity of previously trained models. While a substantial body of work addresses drift detection, identifying that and when a distributional shift has occurred, comparatively fewer studies address root-cause localization: identifying which feature or features are responsible for the shift, information that is essential for targeted retraining, feature-level remediation, and operator trust in automated monitoring pipelines.

Recent work has begun to incorporate explainable AI (XAI) techniques, particularly SHapley Additive exPlanations (SHAP), into drift detection pipelines to support root-cause diagnosis. Hierarchical approaches combine error-rate-based drift signals with SHAP-based feature attribution and drift-point backtracking to localize both when and why a model's behavior has changed. However, existing explainable drift detection frameworks compute SHAP attribution over static, uniformly weighted sliding windows, treating all instances within the window as equally informative regardless of their temporal proximity to the drift event.

Temporal decay weighting, assigning exponentially decreasing importance to older instances, is a well-established mechanism in adaptive learning and has previously been shown to improve predictive performance in non-stationary settings by prioritizing recent evidence. It is therefore a natural hypothesis that decay-weighting SHAP attribution computation would similarly sharpen root-cause localization by emphasizing the instances closest to the drift event. This paper tests that hypothesis directly and systematically, rather than assuming it.

Our central finding runs counter to this intuition. Across a controlled ablation of 456 matched observations spanning three detectors, four decay rates, and three drift types, we find that decay-weighted SHAP (TDW-SHAP) does not improve, and in most configurations significantly degrades, root-cause attribution accuracy relative to standard uniformly weighted SHAP. We further show that this degradation is not uniform but follows an interpretable dose-response relationship with the decay rate lambda, and interacts with drift type in a mechanistically explicable way. We frame this as a cautionary, evidence-based contribution: temporal decay weighting, while valuable for drift detection, requires careful and separate justification when applied to explanation and root-cause attribution tasks, where retaining contrastive pre-drift information appears to matter more than recency emphasis.

1.1 Contributions

(1) We propose TDW-SHAP, an exponential decay-weighted variant of window-based SHAP attribution for concept drift root-cause localization. (2) We design a controlled evaluation protocol with importance-filtered synthetic drift injection that guarantees a theoretically detectable ground-truth root cause, addressing a methodological gap in prior explainable drift detection evaluations. (3) We conduct a systematic ablation across detectors, decay rates, and drift types, and report a statistically robust negative result with a clear dose-response mechanism, offering practical guidance on when temporal weighting should and should not be applied in explainable drift analysis.

2. Related Work

Concept drift detection methods are broadly categorized into error-rate-based detectors (e.g., DDM, EDDM), distribution-based detectors (e.g., ADWIN, KSWIN), and hybrid approaches. These methods reliably flag that drift has occurred but generally do not explain which features drove the shift.

A growing line of work integrates model explainability into drift analysis. Hierarchical frameworks combining error-rate monitoring with SHAP-based feature attribution and drift-point backtracking have been proposed to jointly detect drift and localize its cause, typically using fixed-size sliding windows for attribution computation. Related work in industrial and financial domains has combined distribution-based detectors such as KSWIN with event-triggered SHAP explanation modules, and hybrid frameworks combining SMOTEBoost, DDM and ADWIN, and SHAP and LIME explainability have been proposed for fraud detection under drift. Across this literature, attribution windows are treated as uniformly weighted, and the potential benefit of temporal weighting for the explanation task itself has not been directly tested.

Separately, temporal decay weighting has been used to improve predictive accuracy in non-stationary and streaming settings by emphasizing recent instances during model updates. This paper is, to our knowledge, the first to isolate and test the effect of applying decay weighting specifically to the SHAP attribution computation used for drift root-cause localization, as distinct from its established use in the underlying predictive model.

3. Proposed Method

3.1 Temporal Decay-Weighted SHAP (TDW-SHAP)

Given a detected drift point at stream index d, we define a pre-drift attribution window W of size w consisting of the w instances immediately preceding d. A surrogate model M (Random Forest, n_estimators = 50, max_depth = 6) is fit on W under an instance weighting scheme. For standard SHAP, weights are uniform: c_i = 1 for all i in W. For TDW-SHAP, weights follow exponential decay as a function of recency: c_i = exp(-lambda times (w - t_i)), where t_i is the position of instance i within the window and lambda is the decay rate. TreeExplainer is applied to the fitted surrogate, and mean absolute SHAP value per feature over W is used as the attribution score. The feature with the highest mean absolute SHAP value is treated as the predicted root cause of the drift.

3.2 Ground-Truth-Guaranteed Drift Injection

To enable quantitative evaluation of root-cause attribution accuracy, synthetic drift is injected into the Electricity benchmark at known stream positions, with the responsible feature recorded as ground truth. Three drift types are implemented: sudden (abrupt permutation of a feature's values from the drift point onward), gradual (probabilistic linear transition to permuted values over a fixed-length window), and recurring (alternating between two concept states across multiple drift points). Critically, we restrict eligible injection features to those with baseline Random Forest feature importance at or above the median, computed on a clean, non-drifted sample prior to injection. This addresses a methodological pitfall identified during pilot experiments, in which drift injected into low-importance features (e.g., a feature contributing under 5 percent of baseline importance) produced ground-truth root causes that were, by construction, undetectable by any attribution method, since the surrogate model does not rely on that feature for prediction regardless of its distributional stability.

3.3 Evaluation Protocol

For each combination of drift type (sudden, gradual, recurring), base detector (ADWIN, DDM, KSWIN), and random seed (n = 5), synthetic drift is injected and the detector is run over the full stream. Detected drift points are matched to the nearest true injection point within a tolerance window of 300 instances. For each matched detection, TDW-SHAP and standard SHAP attributions are computed over the preceding window (w = 500), and a hit is recorded if the ground-truth feature appears within the top-k = 3 ranked features. Root-cause attribution accuracy is

aggregated across matched points, and statistical comparison between TDW-SHAP and standard SHAP is performed via paired t-test, since both methods are evaluated on the identical set of matched drift points.

4. Experimental Setup

Dataset: Electricity (Elec2), a widely used non-stationary streaming benchmark comprising approximately 45,000 instances with eight features (nswprice, nswdemand, vicprice, vicdemand, period, date, day, transfer) and a binary class label. Baseline feature importance ranking (Random Forest, n = 2,000 clean samples) identified nswprice (0.386), vicprice (0.165), period (0.137), and nswdemand (0.123) as the four features at or above the median importance threshold, and these were the eligible targets for drift injection.

Detectors: ADWIN, DDM, and KSWIN, as implemented in the River library, each paired with an incrementally trained Hoeffding Tree classifier. Decay rates: lambda in {0.001, 0.01, 0.05, 0.1}, spanning light to aggressive decay. Attribution window size: w = 500 instances. Top-k for hit evaluation: k = 3 (out of 8 total features). All experiments were executed in a CPU-only environment (Google Colab, no GPU acceleration), reflecting the lightweight computational profile of the proposed pipeline; total wall-clock time for the full ablation was approximately 65 minutes.

5. Results

5.1 Overall Comparison

Across all 456 matched drift-detection and explainability observations, standard SHAP achieved a significantly higher overall root-cause attribution accuracy (41.2 percent) than TDW-SHAP (32.7 percent; paired t-test t = -5.42, p < 0.0001). This establishes, at the aggregate level, that decay weighting does not confer a general advantage for root-cause localization under the tested conditions.

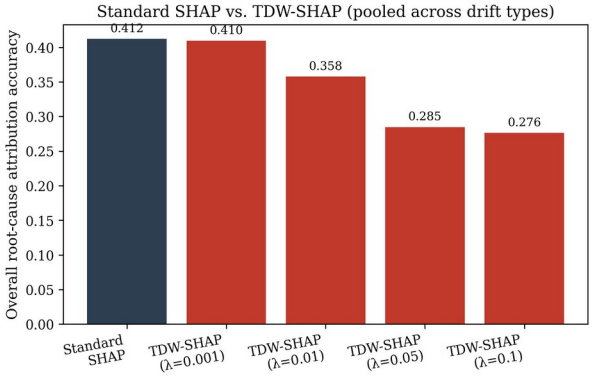

Figure 1. Overall root-cause attribution accuracy: standard SHAP versus TDW-SHAP across decay rates (pooled across drift types and detectors).

5.2 Dose-Response Analysis by Drift Type

Table 1 reports root-cause attribution accuracy stratified by drift type and decay rate. A monotonic dose-response degradation is observed for sudden drift (34.3 percent to 25.7 percent to 20.0 percent to 14.3 percent as lambda increases from 0.001 to 0.1) and for recurring drift (30.2 percent to 23.3 percent to 20.9 percent to 18.6 percent), while standard SHAP remains flat at 37.1 percent and 30.2 percent respectively across all lambda. Gradual drift shows a qualitatively different pattern: TDW-SHAP is statistically indistinguishable from standard SHAP at lambda <= 0.01 (58.3 percent for both), with degradation only emerging at lambda >= 0.05.

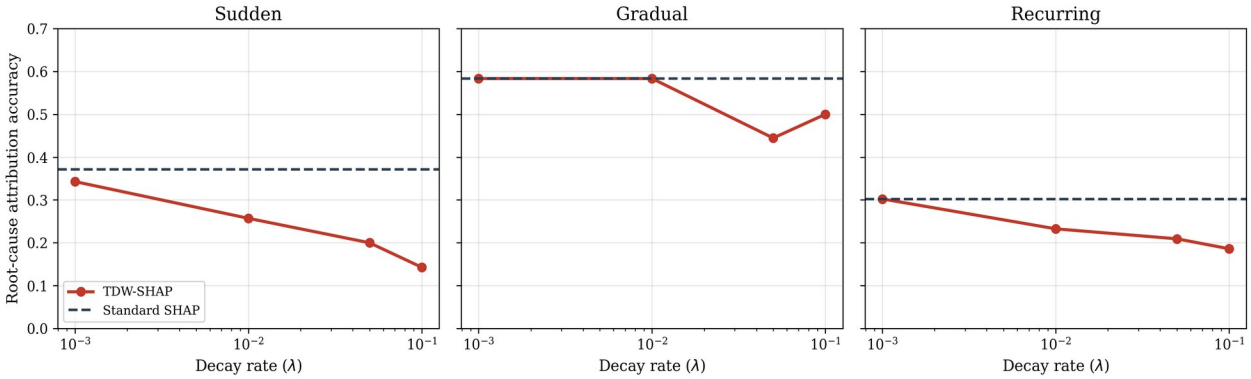

Figure 2. Dose-response relationship between decay rate (lambda) and root-cause attribution accuracy, stratified by drift type. Dashed line indicates the uniform-weighted standard SHAP baseline for that drift type.

Table 1. Root-cause attribution accuracy (TDW-SHAP vs. standard SHAP) by drift type and decay rate.

Drift Type	Lambda	TDW-SHAP Acc.	Standard SHAP Acc.	n
Sudden	0.001	0.343	0.371	35
Sudden	0.010	0.257	0.371	35

Sudden	0.050	0.200	0.371	35
Sudden	0.100	0.143	0.371	35
Gradual	0.001	0.583	0.583	36
Gradual	0.010	0.583	0.583	36
Gradual	0.050	0.444	0.583	36
Gradual	0.100	0.500	0.583	36
Recurring	0.001	0.302	0.302	43
Recurring	0.010	0.233	0.302	43
Recurring	0.050	0.209	0.302	43
Recurring	0.100	0.186	0.302	43

6. Discussion

The dose-response pattern observed across sudden and recurring drift suggests a mechanistic explanation: aggressive decay weighting progressively down-weights and effectively discards pre-drift instances within the attribution window, removing the contrastive signal (the difference between pre- and post-drift feature-target relationships) that the surrogate model requires to correctly attribute the shift. This is conceptually distinct from the role of decay weighting in drift detection itself, where prioritizing recent instances accelerates recognition that a shift has occurred. Root-cause attribution, by contrast, is fundamentally a comparative task between two regimes, and removing evidence of the prior regime undermines rather than assists this comparison.

The relative insensitivity of gradual drift to light decay (lambda <= 0.01) is consistent with this mechanism: because gradual drift itself unfolds as a smooth transition, the window already contains a mixture of old and new concept instances regardless of weighting, so mild decay does not meaningfully alter the contrastive signal available to the surrogate model. Only at higher lambda, where decay becomes aggressive enough to functionally exclude early-window instances, does performance degrade.

From a practical standpoint, these results suggest that practitioners integrating temporal weighting schemes into explainable drift detection pipelines should not assume that mechanisms beneficial for detection transfer directly to explanation. Where root-cause attribution is a priority, uniformly weighted or, at minimum, lightly decayed (lambda <= 0.01) attribution windows are preferable to aggressive decay.

7. Limitations and Future Work

This study evaluates a single benchmark dataset (Electricity) with synthetic drift injection; generalization to naturally occurring drift and to higher-dimensional feature spaces requires further validation. The root-cause hit metric (top-k membership) is categorical and may be insensitive to smaller but meaningful shifts in relative SHAP ranking; continuous metrics such as rank correlation between attribution and ground-truth perturbation magnitude may reveal finer-grained effects. An exploratory drift-type categorization module based on SHAP attribution trajectory features (jump magnitude, slope, oscillation rate) was also developed during this study but did not achieve reliable classification accuracy (25 percent against a three-class random baseline of 33 percent) and is not reported as a core contribution; we note this as a direction for future work, potentially requiring richer trajectory features or a supervised approach trained on a larger labeled corpus of drift trajectories. Finally, this study is restricted to CPU-feasible, lightweight surrogate models and detectors; whether the observed dose-response pattern holds for deep-learning-based streaming classifiers remains an open question.

8. Conclusion

This paper presented a systematic empirical evaluation of temporal decay-weighted SHAP attribution for concept drift root-cause localization. Contrary to the intuitive expectation that recency-weighted explanation would sharpen root-cause diagnosis, we found that decay weighting significantly degrades attribution accuracy overall, with a clear, statistically robust dose-response relationship: light decay is harmless, while aggressive decay is consistently detrimental, particularly for sudden and recurring drift. These findings caution against the uncritical transfer of temporal weighting mechanisms from predictive modeling to explanation tasks, and offer concrete, decay-rate-specific guidance for practitioners designing explainable drift monitoring pipelines.

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