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Editorial Note

Beyond Accuracy: Data Drift, Model Drift and Decision Robustness

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Machine-learning models are commonly evaluated as if the environments in which they operate were stationary. Yet, after deployment, the nature of the problem may change. Customer behaviour evolves, sensors age, markets react, clinical practices change, and cyber adversaries adapt. The growing literature on data and concept drift therefore reflects a broader realization: a model that performed well yesterday cannot automatically be assumed to support reliable decisions tomorrow.

It is useful to distinguish several related phenomena. Data drift describes changes in the distribution of model inputs, P (X). Concept drift occurs when the relationship between inputs and outcomes, P (Y |X), changes. Model drift is often used operationally to describe the resulting deterioration or alteration of a deployed model's predictions, calibration or performance. Note, however, that „model drift"does not necessarily mean its parameters have changed. The distinctions between data drift, concept drift and model drift matter. A change in input data need not harm performance, while serious performance degradation can occur without an easily detectable marginal shift. Moreover, delayed or unavailable labels make real-time detection of concept drift par-ticularly difficult. Recent surveys and benchmarks consequently emphasize unsupervised monitoring, drift localization and explanation, recurrent drift, and adaptive learning [1–4]. The case of confident predictions even when distributions shift has been treated neatly in reference [5].

However, detecting drift is only part of the challenge. Data science systems ultimately influence decisions: allocating resources, approving transactions, prioritizing patients, forecasting demand or identifying cyber threats. A sta-tistically significant distribution shift may be operationally harmless, whereas

a subtle shift affecting a critical subgroup or decision boundary may have se-vere consequences. Recent decision-focused research demonstrates that shifts producing the worst predictive error can differ fundamentally from those pro-ducing the worst downstream decisions [6]. This insight moves the discussion from model robustness toward decision robustness.

A robust data-science system should therefore monitor more than feature distributions and aggregate accuracy. It should track calibration, subgroup performance, uncertainty, decision costs and operational outcomes; test plau-sible stress scenarios; retain human and domain oversight; and specify in ad-vance when a model should be investigated, adapted or withdrawn. In cyber systems, this lifecycle perspective is especially important because drift may be strategic rather than incidental: attackers actively change their behaviour in response to detection.

The emerging research agenda should connect drift detection, causal diag-nosis, adaptive modelling, distributionally robust optimization and decision-focused evaluation. The central question is not only whether the data or model has changed. It is whether the decisions produced by the system re-main safe, effective and defensible under change.

REFERENCES

1. Arora S, Rani R, Saxena N. A systematic review on detection and adaptation of concept drift in streaming data using machine learning techniques. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery. 2024 Jul;14(4):e1536.
2. Hinder F, Vaquet V, Hammer B. One or two things we know about concept drift—a survey on monitoring in evolving environments. Part A: detecting concept drift. Frontiers in Artificial Intelligence. 2024 Jun 19;7:1330257.
3. Hinder F, Vaquet V, Hammer B. One or two things we know about concept drift—a survey on monitoring in evolving environments. Part B: locating and explaining concept drift. Frontiers in Artificial Intelligence. 2024 Jul 19;7:1330258.
4. Lukats D, Zielinski O, Hahn A, Stahl F. A benchmark and survey of fully unsupervised concept drift detectors on real-world data streams. International Journal of Data Science and Analytics. 2025 Jan; 19(1):1-31.
5. Cauchois M, Gupta S, Ali A, Duchi JC. Robust validation: Confident predictions even when distributions shift. Journal of the American Statistical Association. 2024 Oct 1;119(548):3033-44.
6. Ren K, Byun Y, Wilder B. Decision-focused evaluation of worst-case distribution shift. arXiv preprint arXiv:2407.03557. 2024 Jul 4.

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