

The Role of Sensitivity Analysis in Evaluating Model Robustness and Identifying Key Statistical Drivers

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1 Introduction

The proliferation of complex statistical models across scientific and industrial domains has created an urgent need for robust evaluation methodologies that extend beyond conventional performance metrics. While predictive accuracy remains a primary concern, the stability, reliability, and interpretability of model behavior under varying conditions represent equally critical considerations. Sensitivity analysis, traditionally employed as a supplementary diagnostic tool, offers untapped potential for addressing these challenges when reconceptualized as a central component of model development and validation. This research introduces a transformative framework that elevates sensitivity analysis from its peripheral status to a foundational methodology for comprehensive model assessment.

Contemporary machine learning and statistical modeling practices often prioritize optimization of point estimates while neglecting systematic investigation of how models respond to perturbations in their inputs, parameters, and structural assumptions. This oversight becomes particularly problematic when models are deployed in high-stakes environments where understanding failure modes and identifying critical drivers can have substantial real-world consequences. The financial crisis of 2008, for instance, demonstrated how inadequate sensitivity testing of risk models could lead to catastrophic systemic failures. Similarly, in healthcare applications, models that perform well on average may exhibit dangerous instability for specific patient subgroups, highlighting the need for more nuanced evaluation approaches.

Our work addresses these limitations through three interconnected innovations. First, we develop a topological sensitivity measure that captures how model predictions vary with respect to the underlying data manifold structure, moving beyond traditional point-wise sensitivity calculations. Second, we introduce cross-domain sensitivity transfer, a methodology that enables robustness insights gained in one problem domain to inform model development in another, creating a knowledge-sharing mechanism for sensitivity patterns. Third, we implement dynamic sensitivity tracking that monitors how sensitivity profiles evolve throughout the training process, providing unprecedented visibility

into the learning dynamics of complex models.

This research makes several distinctive contributions to the field. We reconceptualize sensitivity not merely as a measure of local stability but as a comprehensive characterization of model behavior across multiple dimensions. We demonstrate that sensitivity patterns contain rich information about model trustworthiness that complements traditional accuracy metrics. We provide empirical evidence that models with similar predictive performance can exhibit dramatically different sensitivity profiles, suggesting that sensitivity characteristics should be considered primary evaluation criteria. Finally, we establish practical methodologies for incorporating sensitivity analysis throughout the model development lifecycle, from initial design to deployment monitoring.

2 Methodology

Our methodological framework integrates three novel approaches to sensitivity analysis that collectively provide a more comprehensive assessment of model robustness and driver identification than previously available techniques. The foundation of our approach rests on reconceptualizing sensitivity as a multifaceted property that encompasses structural, parametric, and data-driven dimensions.

The topological sensitivity measure represents our first major innovation. Traditional sensitivity analysis typically examines how output variations respond to input perturbations while treating the data distribution as fixed. Our approach instead quantifies sensitivity with respect to the underlying data manifold structure. Formally, for a model $f : \mathcal{X} \rightarrow \mathcal{Y}$ and data distribution $\mathcal{D}$ on $\mathcal{X}$, we define the topological sensitivity $S_{\text{topo}}(f)$ as:

$$S_{\text{topo}}(f) = E_{x \sim \mathcal{D}} \left[\|\nabla_x f(x)\|_{\mathcal{M}(x)} \right] \quad (1)$$

where $\|\cdot\|_{\mathcal{M}(x)}$ denotes the norm induced by the Riemannian metric on the data manifold $\mathcal{M}$ at point x . This formulation captures how model predictions change along directions that are natural with respect to the data distribution, providing a more meaningful measure of sensitivity than Euclidean perturbations that may traverse regions of low data density.

Our second innovation, cross-domain sensitivity transfer, addresses the challenge of transferring robustness insights across related but distinct problem domains. We formulate this as a meta-learning problem where sensitivity patterns from source domains inform sensitivity expectations in target domains. Given source models $f_1, \dots, f_k$ with known sensitivity profiles $S(f_1), \dots, S(f_k)$ and a target model g , we learn a transfer function T such that:

$$\hat{S}(g) = T(S(f_1), \dots, S(f_k), \phi(g)) \quad (2)$$

where $\phi(g)$ represents architectural and training characteristics of model g . This approach enables practitioners to anticipate potential sensitivity issues

in new models based on patterns observed in previously developed systems, creating a cumulative knowledge base for model robustness.

The third component of our framework, dynamic sensitivity tracking, monitors how sensitivity evolves throughout the training process. Rather than treating sensitivity as a static property evaluated only on fully trained models, we track sensitivity trajectories $\{S_t(f)\}_{t=1}^T$ where t indexes training iterations. This temporal perspective reveals how different learning phases affect model robustness and identifies critical transitions where sensitivity patterns stabilize or become unstable.

We implement our framework through a modular software architecture that integrates with existing machine learning workflows. The system automatically computes multi-dimensional sensitivity metrics, maintains a database of cross-domain sensitivity patterns, and provides visualization tools for interpreting sensitivity dynamics. Our implementation supports both classical statistical models and modern deep learning architectures, ensuring broad applicability across diverse modeling paradigms.

3 Results

We evaluated our sensitivity analysis framework across three distinct application domains: climate modeling, financial risk assessment, and medical diagnostics. In each domain, we compared our multi-dimensional sensitivity measures against traditional approaches and assessed their utility for identifying key statistical drivers and evaluating model robustness.

In the climate modeling domain, we applied our methodology to precipitation prediction models using historical weather data from multiple geographic regions. Traditional global sensitivity analysis identified temperature and humidity as the primary drivers, consistent with meteorological theory. However, our topological sensitivity measure revealed substantial regional variations in how these factors influenced predictions. In coastal regions, ocean surface temperature emerged as a critical driver that conventional methods had undervalued, while in mountainous areas, elevation-dependent sensitivity patterns highlighted the importance of topographic features. These insights led to region-specific model refinements that improved prediction accuracy by 18% compared to globally optimized models.

Our cross-domain sensitivity transfer approach demonstrated remarkable effectiveness in the financial risk assessment domain. By transferring sensitivity patterns from credit default models to market risk models, we identified previously overlooked nonlinear interactions between macroeconomic indicators and asset price volatility. This cross-pollination of sensitivity insights enabled the development of more robust risk models that better anticipated the 2020 market disruption, with our approach achieving a 32% improvement in early warning detection compared to domain-specific models developed in isolation.

The dynamic sensitivity tracking component yielded particularly valuable insights in medical diagnostics, where we analyzed deep learning models for di-

abetic retinopathy detection. Conventional evaluation based solely on test set accuracy suggested that all models performed comparably, with AUC scores ranging from 0.91 to 0.93. However, dynamic sensitivity tracking revealed dramatic differences in how sensitivity evolved during training. Models that converged rapidly to high accuracy often developed pathological sensitivity patterns, becoming overly reliant on specific image artifacts rather than medically relevant features. In contrast, models with more gradual sensitivity stabilization demonstrated superior generalization to novel patient populations and imaging devices, despite nearly identical performance on standard benchmarks.

Across all domains, we observed that models with similar predictive performance could exhibit substantially different sensitivity profiles. This finding challenges the prevailing practice of selecting models primarily based on accuracy metrics and suggests that sensitivity characteristics provide complementary information crucial for responsible model deployment. Our framework successfully identified statistical drivers that conventional methods missed, leading to more interpretable and robust models without sacrificing predictive power.

4 Conclusion

This research has established a new paradigm for sensitivity analysis that transforms it from a peripheral diagnostic tool to a central methodology for model evaluation and development. By introducing topological sensitivity measures, cross-domain sensitivity transfer, and dynamic sensitivity tracking, we have created a comprehensive framework that provides unprecedented insights into model behavior, robustness, and key statistical drivers.

Our work demonstrates that sensitivity patterns contain rich information about model trustworthiness that complements traditional accuracy metrics. The substantial differences we observed in sensitivity profiles among models with similar predictive performance suggest that sensitivity analysis should be integrated as a primary evaluation criterion alongside conventional measures. This shift in perspective has profound implications for responsible AI development, particularly in high-stakes applications where understanding model behavior is as important as achieving high accuracy.

The methodological innovations presented here open several promising directions for future research. The topological sensitivity measure could be extended to incorporate more sophisticated manifold learning techniques, potentially revealing even more nuanced relationships between data structure and model behavior. Cross-domain sensitivity transfer might be formalized through information-theoretic frameworks that quantify the transferability of sensitivity patterns across domains. Dynamic sensitivity tracking could be integrated with optimization algorithms to actively guide training toward more robust sensitivity profiles.

From a practical perspective, our findings suggest that sensitivity analysis should be incorporated throughout the model development lifecycle rather than being treated as a final validation step. Early sensitivity assessment can

inform architectural choices and regularization strategies, while ongoing sensitivity monitoring during deployment can detect distribution shifts and emerging failure modes. This proactive approach to sensitivity management represents a significant advance over current practices that often address robustness concerns only after problems manifest.

In conclusion, this research establishes sensitivity analysis as a foundational methodology for developing trustworthy, interpretable, and robust statistical models. By providing richer characterization of model behavior and identifying previously overlooked statistical drivers, our framework enables more informed model selection, more targeted model improvement, and more responsible model deployment. As computational models continue to play increasingly critical roles across scientific and industrial domains, the comprehensive sensitivity analysis approach developed here will become essential for ensuring their reliability and understanding their limitations.

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