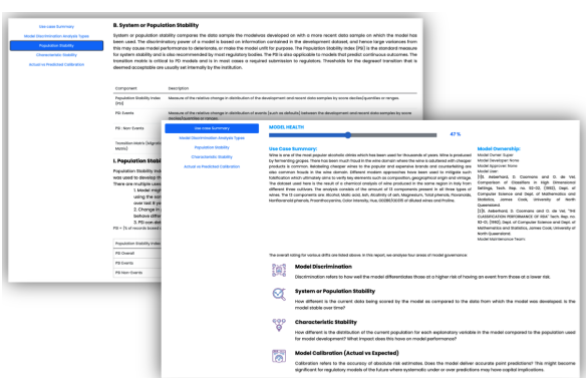
Model Governance Reporting: A Deep Dive into the Hexagon-ml Framework



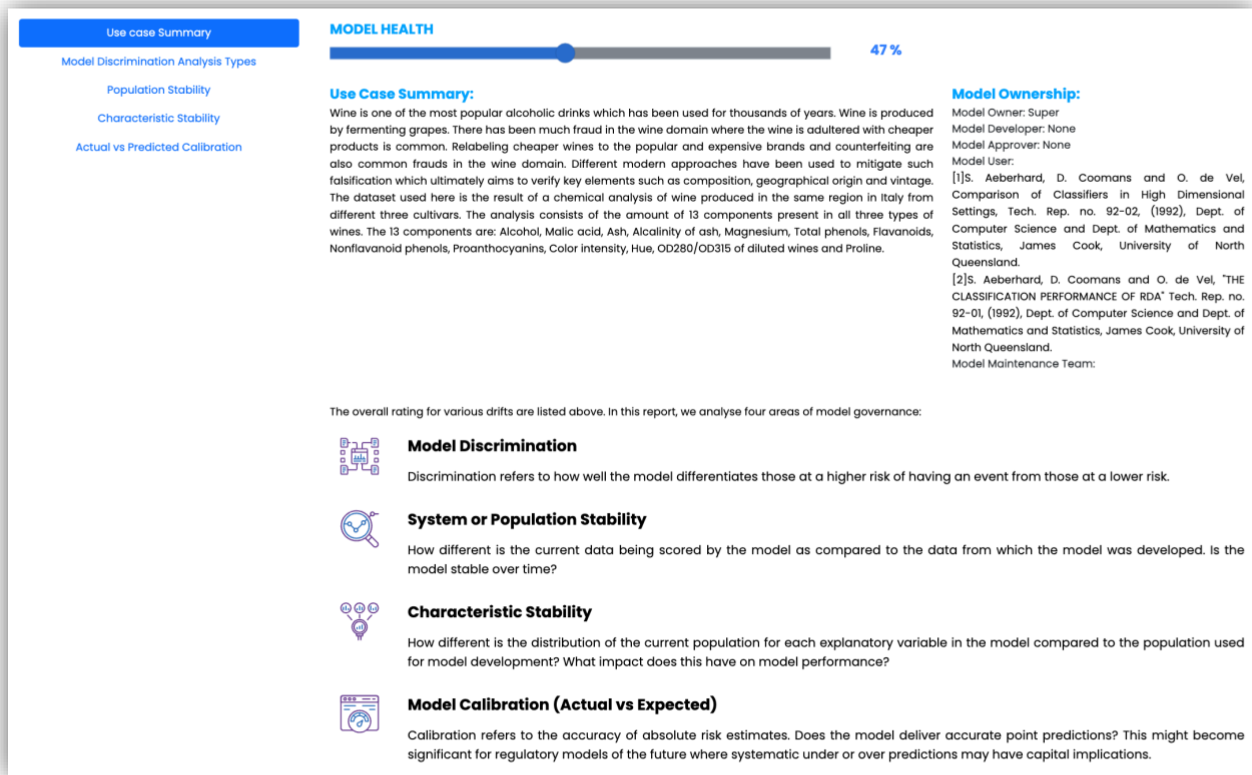
In our modern, model and data-centric era, the influence of machine learning and artificial intelligence (AI) is undeniable. These technologies power a vast array of applications, ranging from diagnosing diseases in healthcare to predicting financial market trends. As the reliance on these models grows, especially in critical decision-making areas, there's a heightened emphasis on model governance. This concept pertains to the meticulous management and regular oversight of AI and machine learning models to ensure their effectiveness and fairness.

Hexagon-ml framework is a pioneering solution in this domain. This framework provides an all-encompassing methodology for model governance. It doesn't just focus on the accuracy of predictions but also delves into the ethical implications and reliability of models. By adopting the Hexagon-ml approach, organizations can ensure that their AI models function optimally, adhere to ethical standards, and remain dependable over time. This deep dive into the framework's components underscores its significance in today's AI-driven landscape.

Hexagon-ml’s Model Governance Framework

Model Discrimination
At its core, model discrimination is about discerning differences. Imagine a security system trained to differentiate between employees and intruders. If it can't accurately tell one from the other, it's not very useful. Similarly, in machine learning, a model's ability to distinguish between different outcomes or classes is vital.

Hexagon-ml's Take:
The Hexagon-ml framework places a strong emphasis on model discrimination. It provides tools and metrics to measure how well a model can differentiate between varying risk levels or outcomes. By ensuring high discrimination, models can make more accurate predictions, leading to better outcomes and more informed decision-making processes. Moreover, in sectors like finance or healthcare, where stakes are high, a model's discriminatory power can have profound implications, affecting everything from patient treatments to investment decisions.

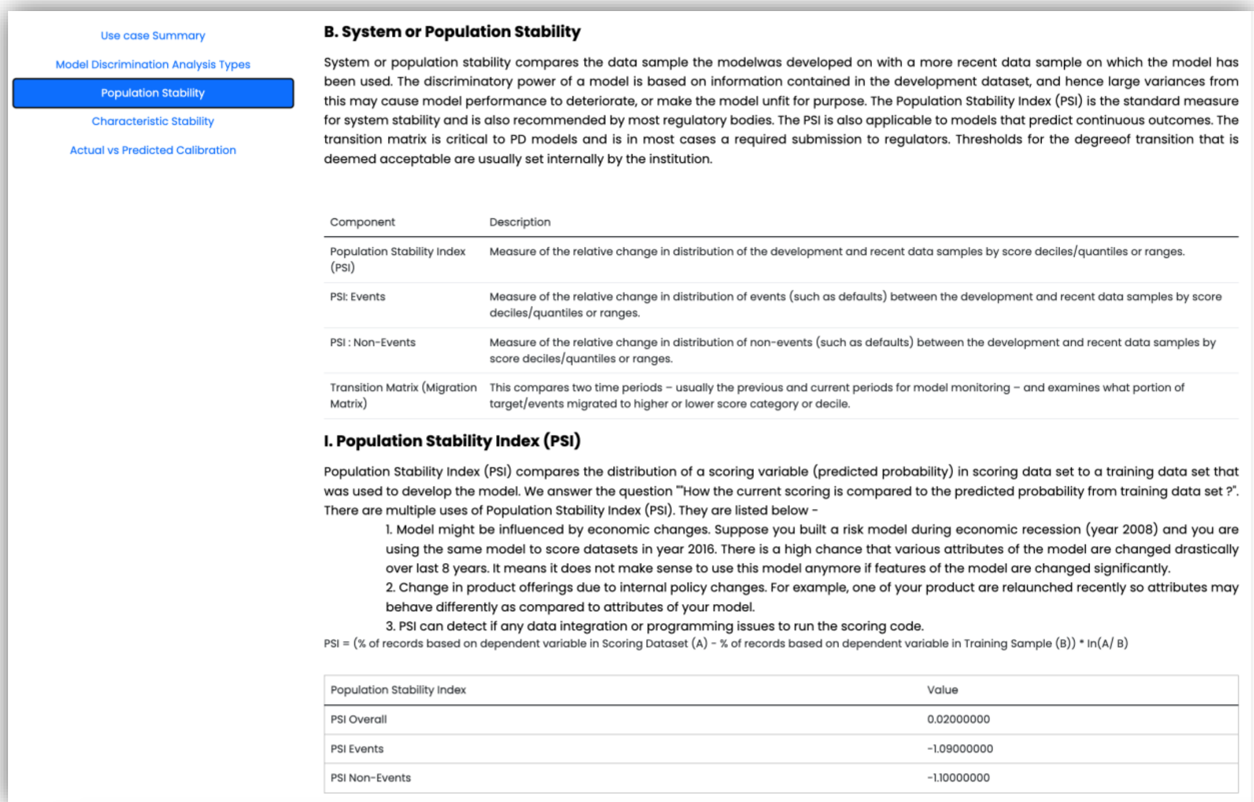


System or Population Stability

Think of a model as a plant that thrives in a specific type of soil. If the soil's composition changes drastically, the plant might struggle to grow. Similarly, a model trained on a specific dataset might falter if the current data it's analyzing deviates significantly from its training data.

Hexagon-ml's Perspective:

Recognizing the importance of data consistency, the Hexagon-ml framework offers tools to monitor and assess data stability. By regularly comparing current data with training data, organizations can identify potential drifts or shifts. This proactive approach ensures that models remain relevant and effective, even as data landscapes evolve. In dynamic sectors, where data can change rapidly, such as e-commerce or social media, ensuring system or population stability is crucial for maintaining model accuracy and reliability.



Use case Summary
Model Discrimination Analysis Types
Population Stability
Characteristic Stability
Actual vs Predicted Calibration

B. System or Population Stability

System or population stability compares the data sample the modelwas developed on with a more recent data sample on which the model has been used. The discriminatory power of a model is based on information contained in the development dataset, and hence large variances from this may cause model performance to deteriorate, or make the model unfit for purpose. The Population Stability Index (PSI) is the standard measure for system stability and is also recommended by most regulatory bodies. The PSI is also applicable to models that predict continuous outcomes. The transition matrix is critical to PD models and is in most cases a required submission to regulators. Thresholds for the degreeof transition that is deemed acceptable are usually set internally by the institution.

Component	Description
Population Stability Index (PSI)	Measure of the relative change in distribution of the development and recent data samples by score deciles/quantiles or ranges.
PSI: Events	Measure of the relative change in distribution of events (such as defaults) between the development and recent data samples by score deciles/quantiles or ranges.
PSI : Non-Events	Measure of the relative change in distribution of non-events (such as defaults) between the development and recent data samples by score deciles/quantiles or ranges.
Transition Matrix (Migration Matrix)	This compares two time periods – usually the previous and current periods for model monitoring – and examines what portion of target/events migrated to higher or lower score category or decile.

I. Population Stability Index (PSI)

Population Stability Index (PSI) compares the distribution of a scoring variable (predicted probability) in scoring data set to a training data set that was used to develop the model. We answer the question ""How the current scoring is compared to the predicted probability from training data set ?". There are multiple uses of Population Stability Index (PSI). They are listed below -

1. Model might be influenced by economic changes. Suppose you built a risk model during economic recession (year 2008) and you are using the same model to score datasets in year 2016. There is a high chance that various attributes of the model are changed drastically over last 8 years. It means it does not make sense to use this model anymore if features of the model are changed significantly.
2. Change in product offerings due to internal policy changes. For example, one of your product are relaunched recently so attributes may behave differently as compared to attributes of your model.
3. PSI can detect if any data integration or programming issues to run the scoring code.

PSI = (% of records based on dependent variable in Scoring Dataset (A) - % of records based on dependent variable in Training Sample (B)) * ln(A/ B)

Population Stability Index	Value
PSI Overall	0.02000000
PSI Events	-1.09000000
PSI Non-Events	-1.10000000

Characteristic Stability

Every dataset has unique features or characteristics. For a model analyzing car sales, these might include car type, price, or fuel efficiency. But what happens if, over time, electric cars become more prevalent, introducing new features like battery life or charging speed?

Hexagon-ml's Approach:

The framework provides robust tools to monitor the stability of data features. By comparing the distribution of features in current data with training data, the Hexagon-ml framework can flag significant discrepancies. This allows data scientists to adjust models, ensuring they remain attuned to current trends and realities. In industries undergoing rapid transformation, such as renewable energy or digital marketing, characteristic stability is vital for ensuring models stay relevant and effective.

Model Calibration (Actual vs Expected)

Imagine a weather prediction model that consistently forecasts rain, even on clear days. Such a model would be poorly calibrated. In machine learning, calibration ensures that a model's predictions align closely with real-world outcomes.

Hexagon-ml's Insight:

The framework offers a nuanced approach to model calibration. By comparing model predictions with actual outcomes, it ensures models remain on track. This is especially crucial for regulatory models, where even slight deviations can have significant repercussions. For instance, in the banking sector, a poorly calibrated credit risk model could lead to substantial financial losses.

In the intricate world of AI and machine learning, the Hexagon-ml framework stands out as a beacon of robust model governance. By addressing key components like discrimination, stability, and calibration, it ensures models are not only accurate but also ethical, reliable, and attuned to current data trends. As organizations increasingly rely on AI-driven insights and predictions, frameworks like Hexagon-ml will play a pivotal role in shaping the future, ensuring that AI models remain trustworthy, effective, and aligned with evolving data landscapes.

References

- Sandeep Reddy, Sonia Allan, Simon Coghlan, Paul Cooper, A governance model for the application of AI in health care, Journal of the American Medical Informatics Association, Volume 27, Issue 3, March 2020, Pages 491–497, https://doi.org/10.1093/jamia/ocz192

- Gasser, Urs, and Virgilio AF Almeida. "A layered model for AI governance." IEEE Internet Computing 21.6 (2017): 58-62.

- Finger, M. and Pécoud, G., 2003. From e-Government to e-Governance? Towards a model of e-Governance. Electronic Journal of E-government, 1(1), pp.pp52-62.

- Sridhar, V., Subramanian, S., Arteaga, D., Sundararaman, S., Roselli, D. and Talagala, N., 2018. Model governance: Reducing the anarchy of production {ML}. In 2018 USENIX Annual Technical Conference (USENIX ATC 18) (pp. 351-358).