Author Feedback to ICML '22 Paper #3404

Dear reviewers, many thanks for the feedback and constructive comments; they greatly appreciate and help us learn and improve. Overall, the reviewers appreciated the importance of the problem, the premise of the paper, and the interest in the approach.

We are optimistic that our rebuttal can address each reviewer's concerns.

General remark

This paper's primary focus is on a small to medium-sized tabular dataset—a very common type of dataset in the average industry. For medium-scale tabular data, non-deep learning-based models achieve SOTA results [1]. This can be made more explicit, if accepted, in a camera-ready version.

[1] Borisov, Vadim, et al. "Deep neural networks and tabular data: A survey." arXiv preprint arXiv:2110.01889 (2021).

Reviewer #1: Real-life example of non-deterioration

The first reviewer asked the following question:

> Can you provide a real-world example or motivating example where the distribution shifts but the model will not or does not deteriorate?

Our third experiment can be seen as an example of this case, wherein a random feature gets shifted. A more realistic example of this phenomenon happens in the house regression problem, where the age of the garage has an insignificant effect on the price of the house. The age of a garage will naturally shift, thus triggering monitoring systems based on distribution shift, but as no performance drop happens, this is not an instance of model deterioration.

Reviewer #4: Hyperparameters

The fourth reviewer states that we did not mention the hyperparameters used. While this is correct, we did mention that we used the default hyperparameters used in the scikit-learn library. To ensure that this is reproducible, we will include the scikit-learn version that we used, as well as include a table with all the hyperparameters in the appendix.

Reviewer #1: Dataset Shift paper

The first reviewer mentioned Rabanser et al. [2] as a paper we need to compare our method to. While being on the topic of distribution shift, the paper is tackling a different problem, as they are focused on deep learning methods and non-tabular datasets. The idea of monitoring the latent space is very interesting, an approach that deserves further research. Unfortunately, non-DL models do not have an easily accessible latent space. Also, the latent space will require distributions, and we are monitoring models at the level of individual predictions. We note that they also mention the Kolmogorov-Smirnov test as a competing method in their statistical hypothesis testing section.

[2] Rabanser, Stephan, Stephan Günnemann, and Zachary Lipton. "Failing loudly: An empirical study of methods for detecting dataset shift." Advances in Neural Information Processing Systems 32 (2019).

Reviewers #2, #3 and #4: Uncertainty estimation

The second, third, and fourth reviewer highlighted alternative uncertainty estimation methods. However, to the best of our knowledge, there are no model agnostic methods that allow us to estimate uncertainty besides those that we compare our method with. Neither, on the application of uncertainty estimation to detect model deterioration.

All reviewers: Performance and ablation studies

All reviewers asked about performance and/or ablation studies. We will add a computational performance comparison to the appendix, along with other simple ablation studies that can help to clarify the contributions.

Appendix

Synthetic data

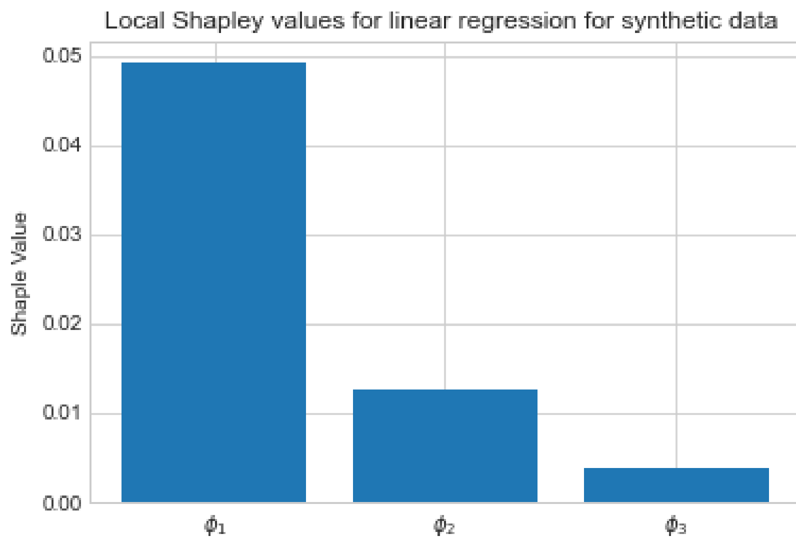
For this case, we create a three-variate normal distributions $X = (X_1, X_2, X_3) \sim N(1, 0.1 \cdot I_3)$, where I_3 is an identity matrix of order three. The target variable is generated $Y = X_1 \cdot X_1 + X_2 + \epsilon$, with $\epsilon \sim N(0, 0.1)$, to have a non linear feature, a linear feature and a non used feature. For both, training and test data, $10,000$ samples are drawn. Then out-of-distribution data is created by shifting X by $\forall j \in \{1, 2, 3\} : X_j^{ood} = X_j^{tr} + 10$.

We train a linear regression model f_θ on $\{X^{tr}, Y^{tr}\}$, and calculate the uncertainty using Doubt (cf. Section XX). We then train another linear model g_θ on

$\{X^{te}, X^{ood}\}$ and the uncertainty estimates. The coeficcients of the linear model are $\beta_1 = 0.0615, \beta_2 = 0.0015, \beta_3 = 0.004$

Since the features are independent and the used model is a linear regression we can calculate the interventional conditional expectation Shapley values as $\phi_i(g_\theta, x) = \beta_i(x_i - \mu_i)$ [3].

So for the data point $x = \{10, 10, 10\}$. The Shapley values are $\phi_i(g_\theta, x)) = \{0.050, 0.012, 0.003\}$ The most relevant shifted feature in the model is the one that receives the highest Shapley value.



[3]Chen, H., Janizek, J. D., Lundberg, S., & Lee, S. I. (2020). True to the Model or True to the Data?. arXiv preprint arXiv:2006.16234.