Screening and Interpreting Inputs in Machine Learning of Additive Manufacturing Systems

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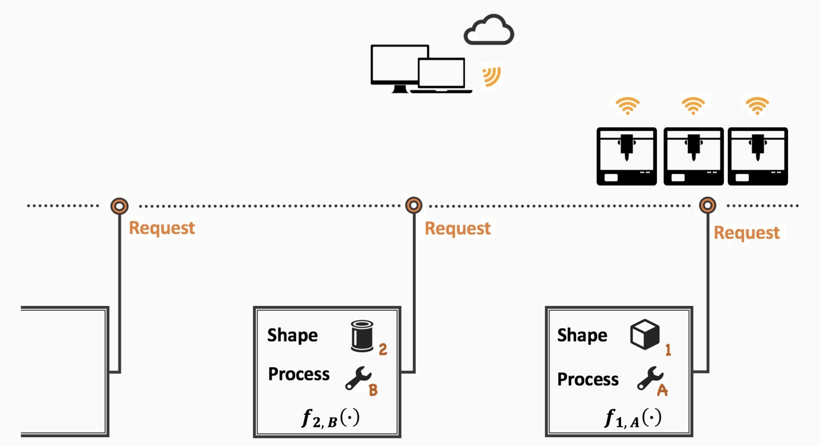
Interpretable ML for CPAMS



A significant trajectory of additive manufacturing (AM) technologies is cyber-physical AM systems (CPAMS) that seamlessly integrate computer-aided design models and physical AM processes.

The future growth and adoption of CPAMS is negatively impacted by geometric shape deviations that are introduced by AM processes.

Machine learning (ML) algorithms have been developed that enable automated deviation modeling from point cloud data collected across processes and shapes in CPAMS (Ferreira, Sabbaghi, and Huang, 2018).

Of critical importance in the application of ML for CPAMS is interpreting the inputs identified as relevant, and their learned associations.

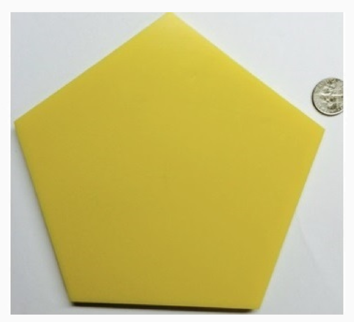
Current interpretability methods for ML have several disadvantages.

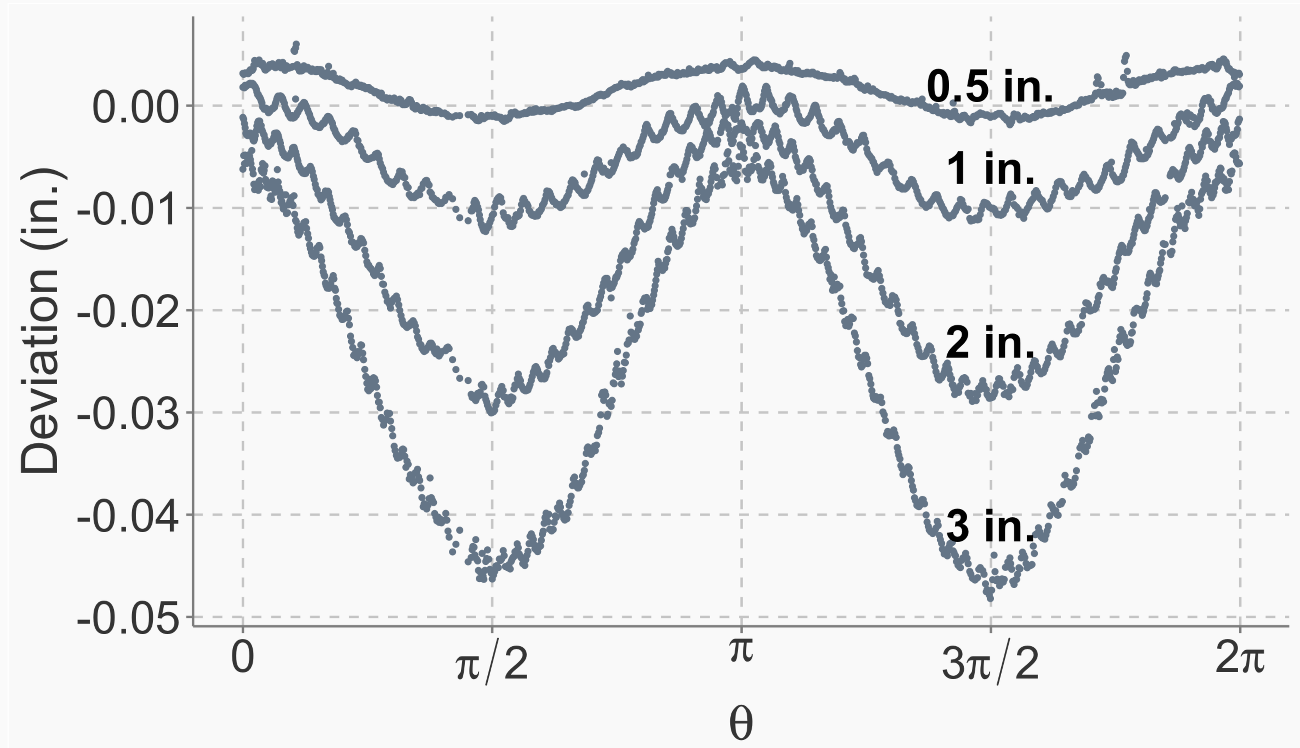
- Focus on single predictions and small domain regions.
- Inability to assess interactions or non-monotonic relationships.

Aim: Global Interpretability for CPAMS

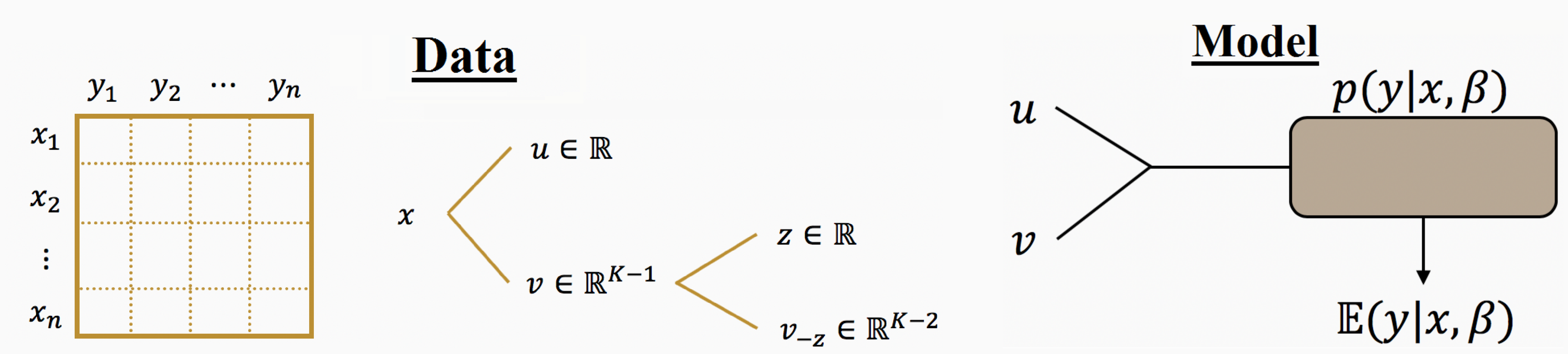
Informative ML of CPAMS requires comprehensible, global interpretations of complex relationships between inputs and geometric shape deviations.

We developed a predictive comparison methodology for global interpretability of ML algorithms that can identify inputs considered to be relevant, and associations learned between inputs and deviations.

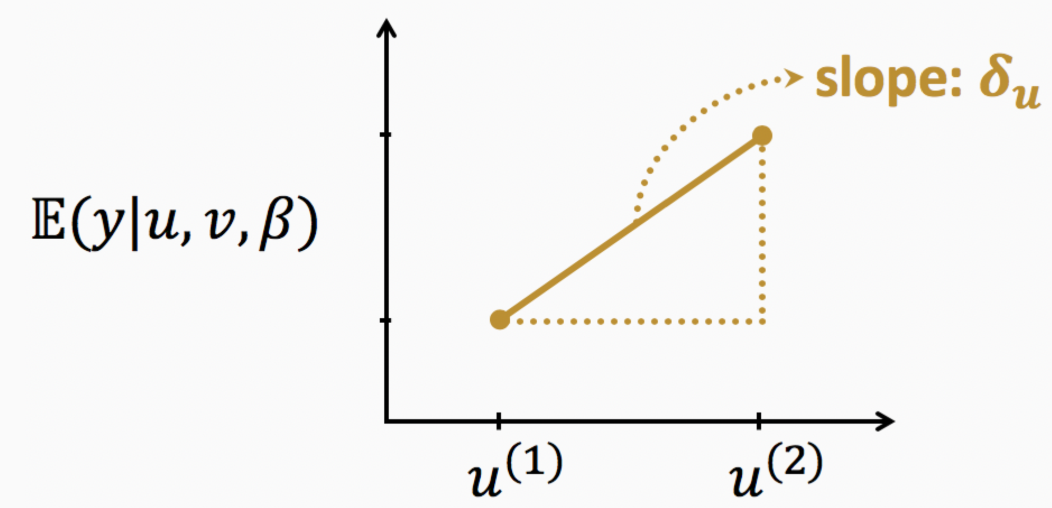




Background and Notation



Average Predictive Comparison Δ_u
Weighted average of slope δ_u over all v, β, and positive $u^{(1)} \to u^{(2)}$.



Screening Relevant Inputs

Average Magnitude Predictive Comparison $\Delta_{\text{mag}(u)}$
Square root of the weighted mean of $(\delta_u)^2$ over all v, β, and $u^{(1)} \to u^{(2)}$.

Relevance: $R\left(\widehat{\Delta}_{\text{mag}(u)}\right) = \widehat{\Delta}_{\text{mag}(u)} \Big/ \sum_{k=1}^{K} \widehat{\Delta}_{\text{mag}(k)}.$

Higher relevance is assigned to higher changes in the output.

Average Sum of Squares Predictive Comparison Λ_u
Square root of the variability between predictions and baseline.

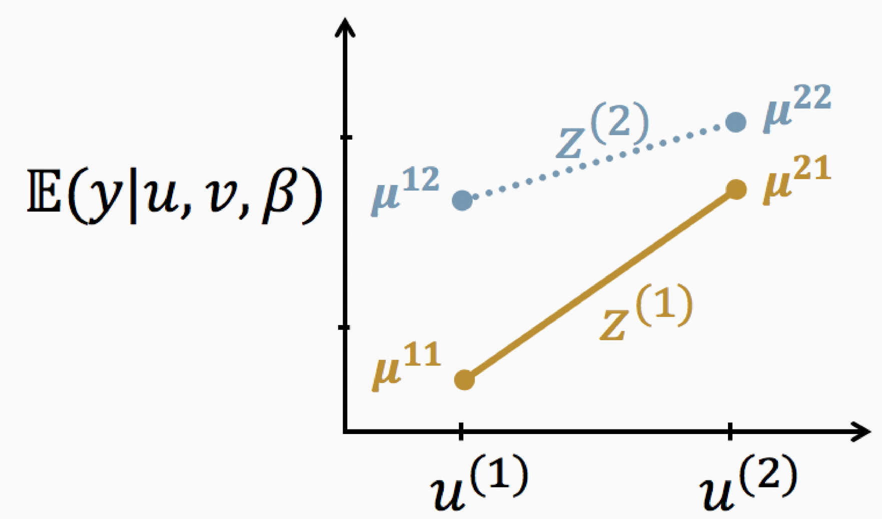
Relevance: $R\left(\widehat{\Lambda}_u\right) = \widehat{\Lambda}_u \Big/ \sum_{k=1}^{K} \widehat{\Lambda}_k.$

Higher relevance is assigned to higher variation between predicted outputs and an average baseline.

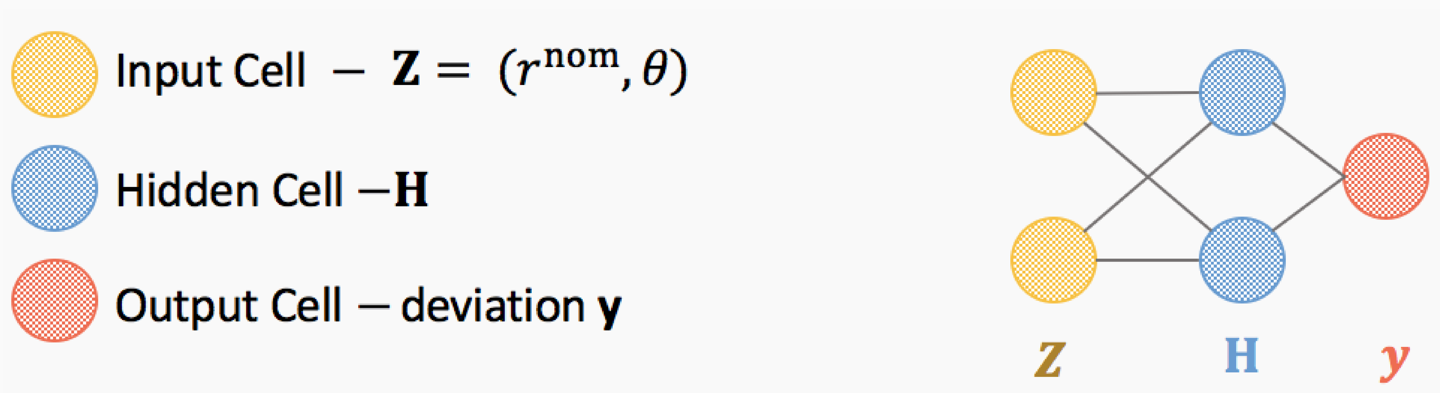
Conditional and Interaction Comparisons

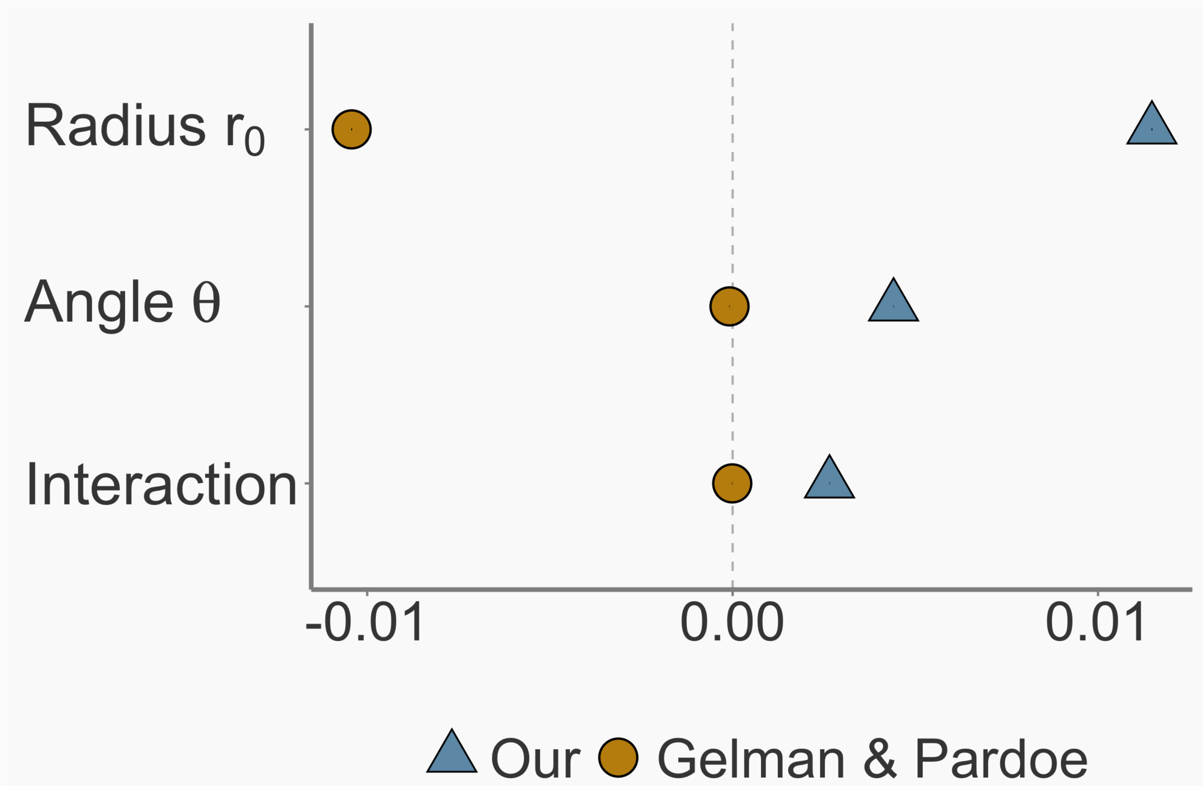
Average Conditional Predictive Comparison $\Delta_{u|z}$
Weighted mean of δ_u over all $\mathbf{v}_{-\mathbf{z}}$, β, and positive $u^{(1)} \to u^{(2)}$, conditional on different levels of $\mathbf{z}$.

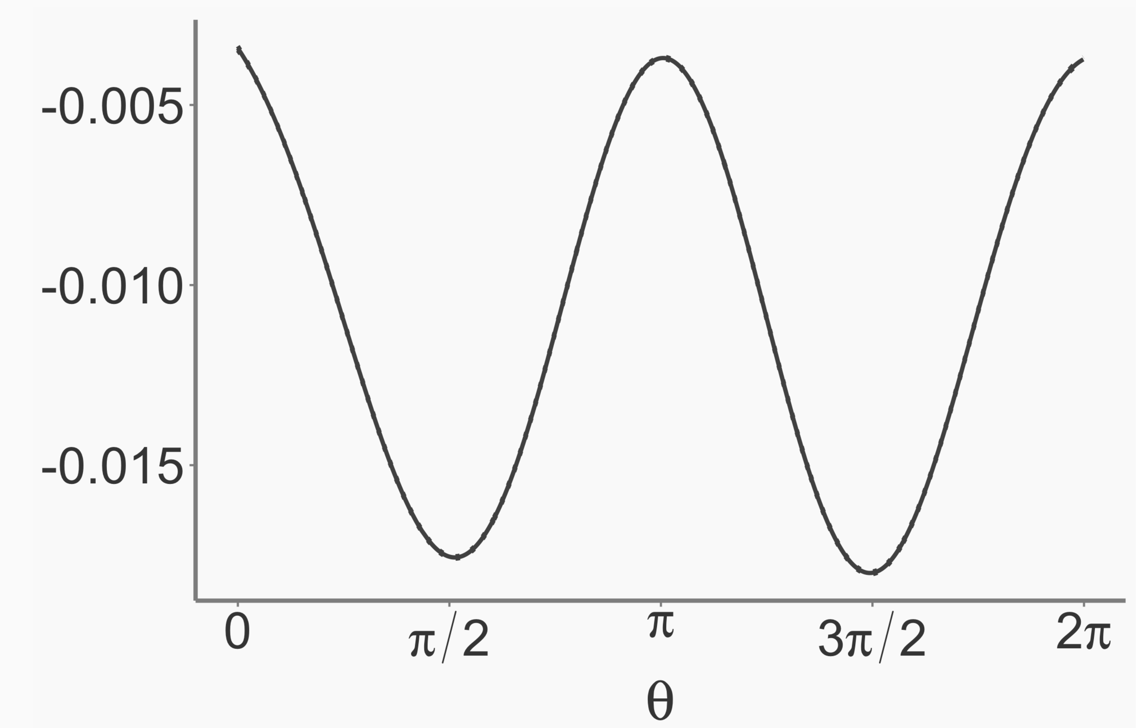
Average Two-Factor Interaction Predictive Comparison $\Delta_{u \times z}$
Weighted mean of $\delta_{\mathbf{u} \times \mathbf{z}}$ over all $\mathbf{v}_{-\mathbf{z}}$, β, and positive $u^{(1)} \to u^{(2)}$ and $z^{(1)} \to z^{(2)}$.



Application: Interpreting NN for SLA







Broader Impact

Our new predictive comparison methodology enables effective screening and interpretations of the effects of inputs on CPAMS that are learned from any complex, black box ML algorithm.

It supplements existing methods, e.g., the framework of Pardoe and Gelman (2007).

The broader impact of our methodology is more informative understanding of general CPAMS, with the potential of immediate practical application for a large community of AM users.

Our methodology also possesses a broad scope of application to any ML algorithm that yields predictions of outcomes and enables samples of β.

Acknowledgments

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