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Can Machine Learning and Explainable Artificial Intelligence Help to Improve an Expert Model for Predicting Thermomechanical Fatigue?

URAI – 2024

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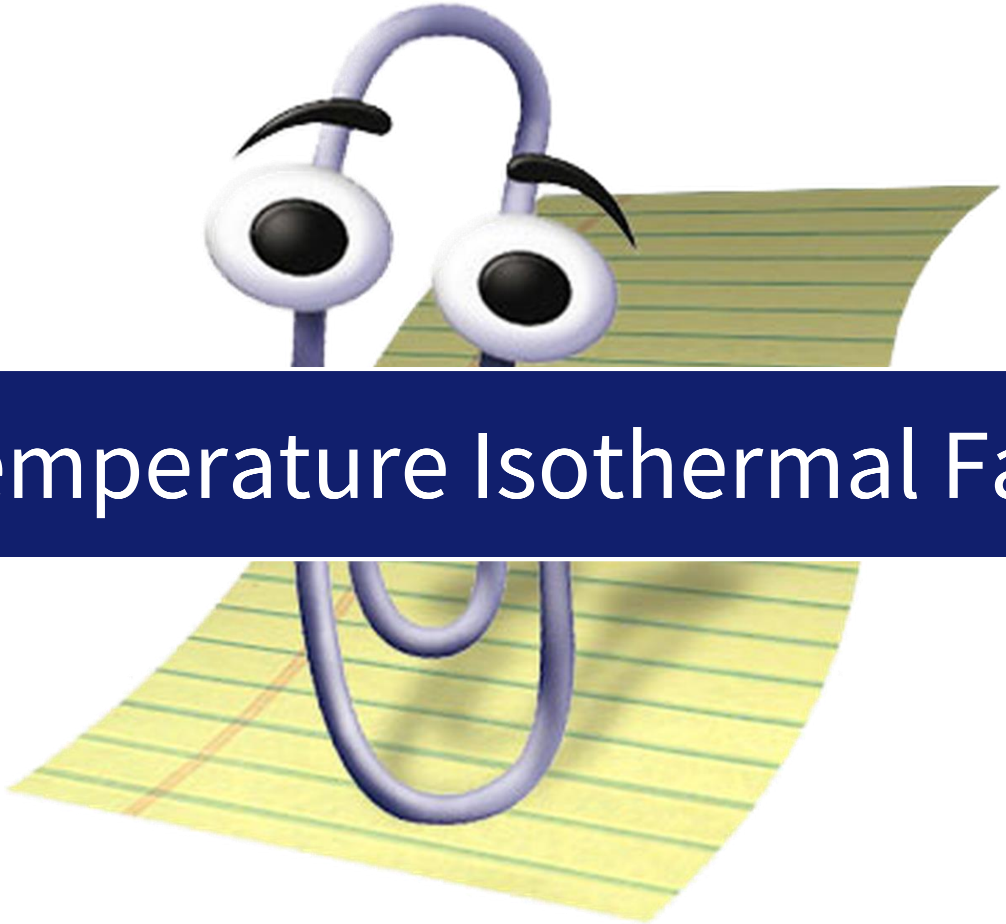
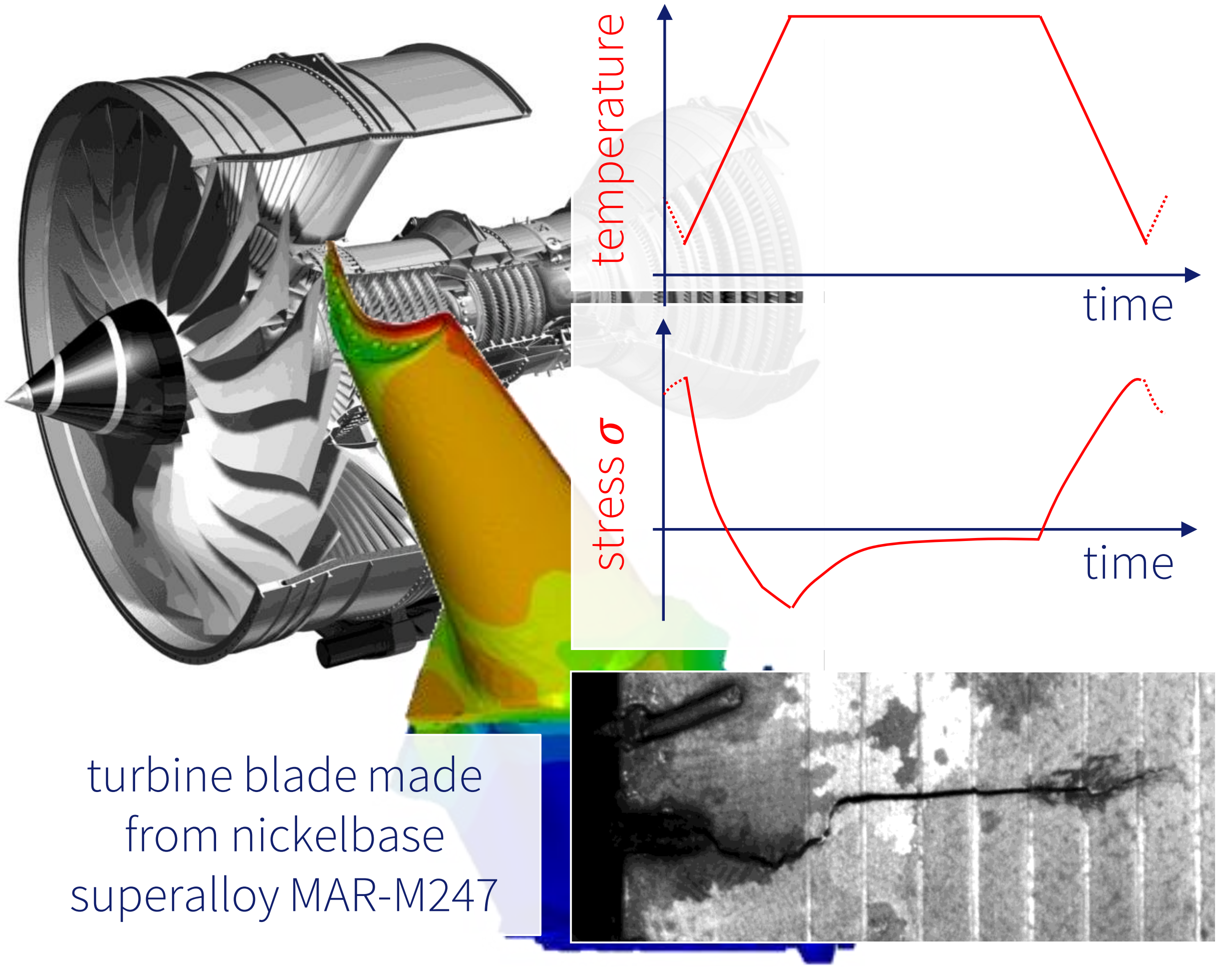
Mechanical Fatigue
Domain background



Low Temperature Isothermal Fatigue

Image: Microsoft Clippy

Motivation
Domain background



turbine blade made from nickelbase superalloy MAR-M247

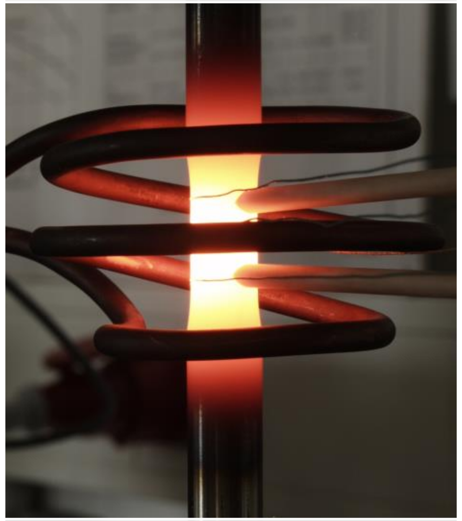
Thermomechanical fatigue (TMF) limits the lifetime of high temperature components:

- Heat-up and cool-down cycles result in stresses in the material.
- Stresses initiate TMF cracks that grow due to **fatigue** and **creep** damage mechanisms during service until they reach a technical critical length.
- **Models** are used for the prediction of the **number of cycles to failure N_f** of components.

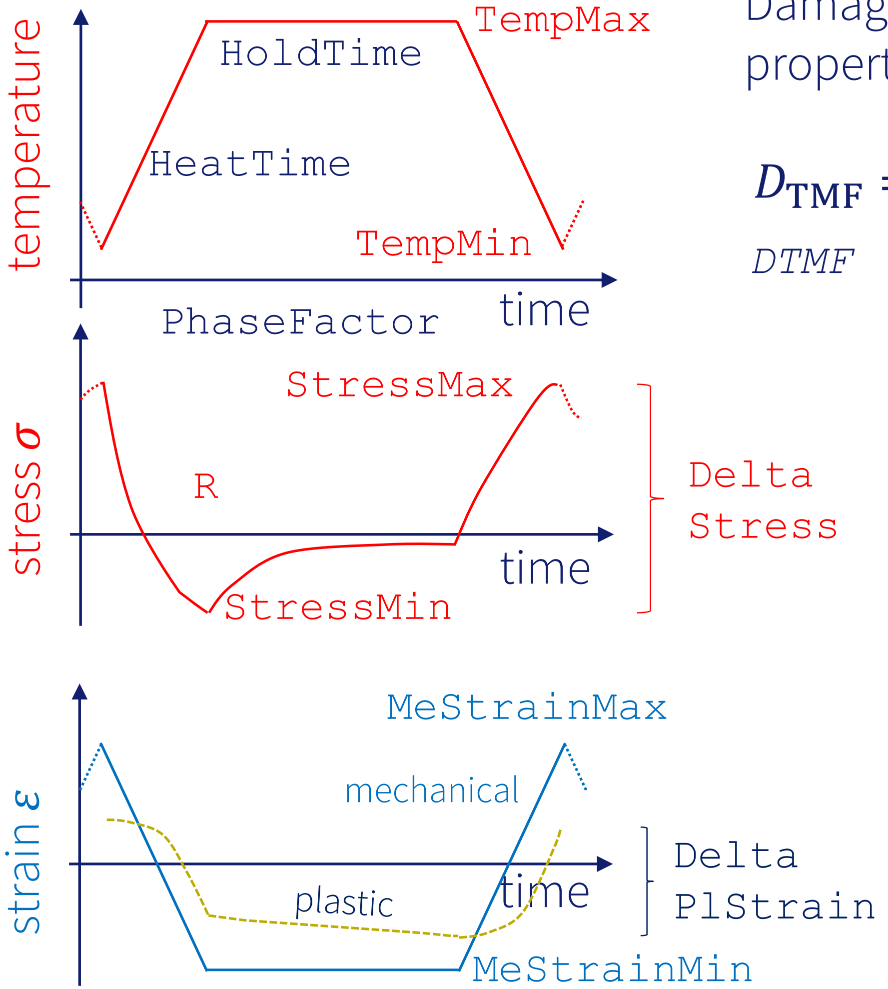
Expert model and features

Simple and expert features

material tests with variation of simple features.



specimen made from nickelbase superalloy MAR-M247



Damage parameter calculated from material properties and load characteristics:

$$D_{\text{TMF}} = \left(1.45\,\frac{\Delta\sigma_{\text{eff}}^2}{E\,\sigma_{CY}} + \frac{2.4}{\sqrt{1+3n'}}\,\frac{\Delta\sigma\Delta\varepsilon^p}{\sigma_{CY}}\right)F_{\text{creep}}$$

DTMF

Material properties: E, SigmaCY, ROHardCy

Correlation of damage parameter with number of cycles to failure with fitting parameters:

$$N_f = \frac{A}{D_{\text{TMF}}^B}$$

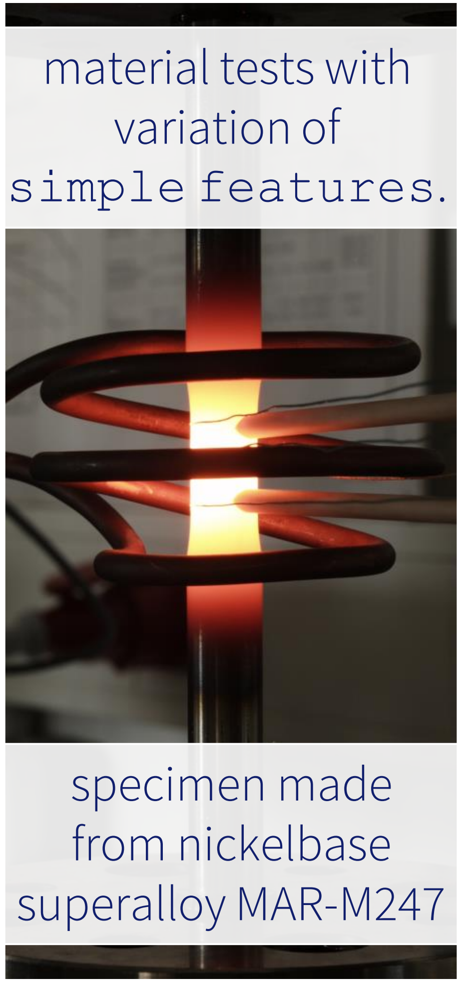
Damage portion due to fatigue:

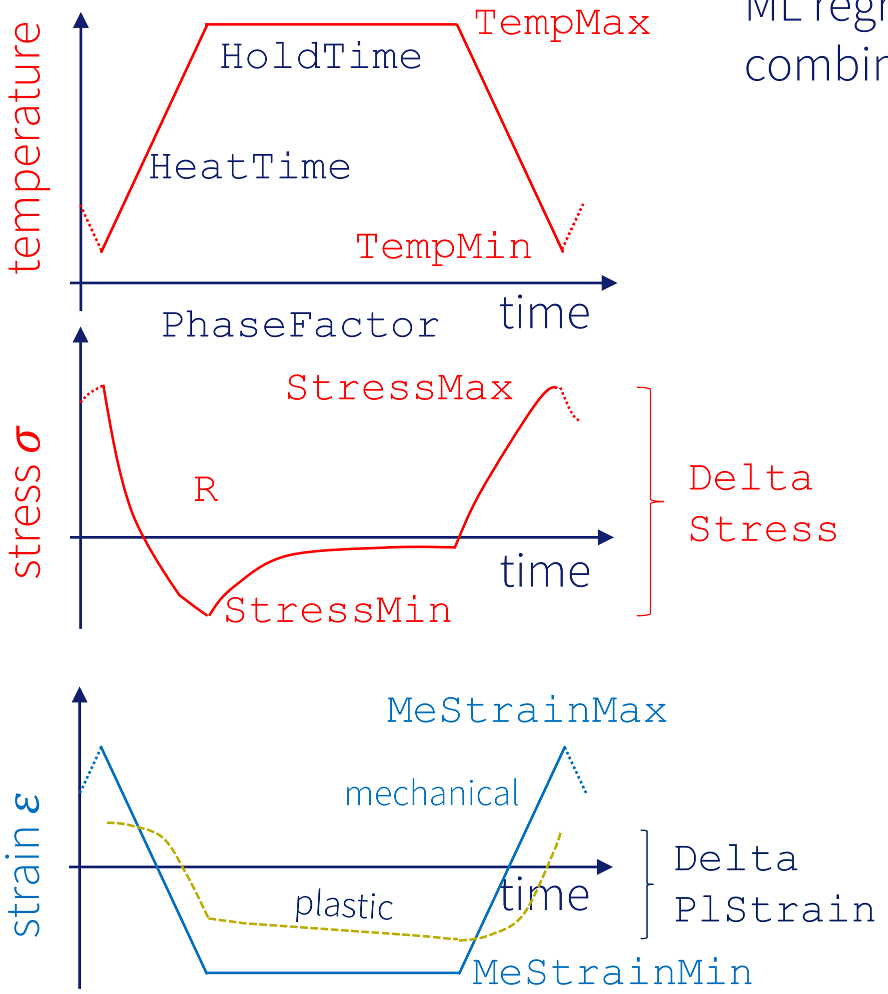
$$D_{\text{fat}} = \frac{1}{F_{\text{creep}}^B}$$

Dfat

ML model and features

Simple and expert features





ML regression model with `simple features` and combined with *`expert features`*:

$\sigma_{CY}, E, n', \Delta\sigma, \Delta\sigma_{\text{eff}}, \ldots, D_{\text{fat}}, \Delta\varepsilon^{p}, D_{\text{TMF}}$

ML Regressor
(Random Forest, SVR, ...)

$log_{10}(N_f)$

Model Evaluation

Dataset

- 185 isothermal and
- 117 thermomechanical experiments

Error Function

$$\text{RMSL10E} = \sqrt{\sum_i \left(\log_{10}(N_{f_i}) - \log_{10}(\hat{N}_{f_i})\right)^2}$$

- Error factor more important than absolute error value!

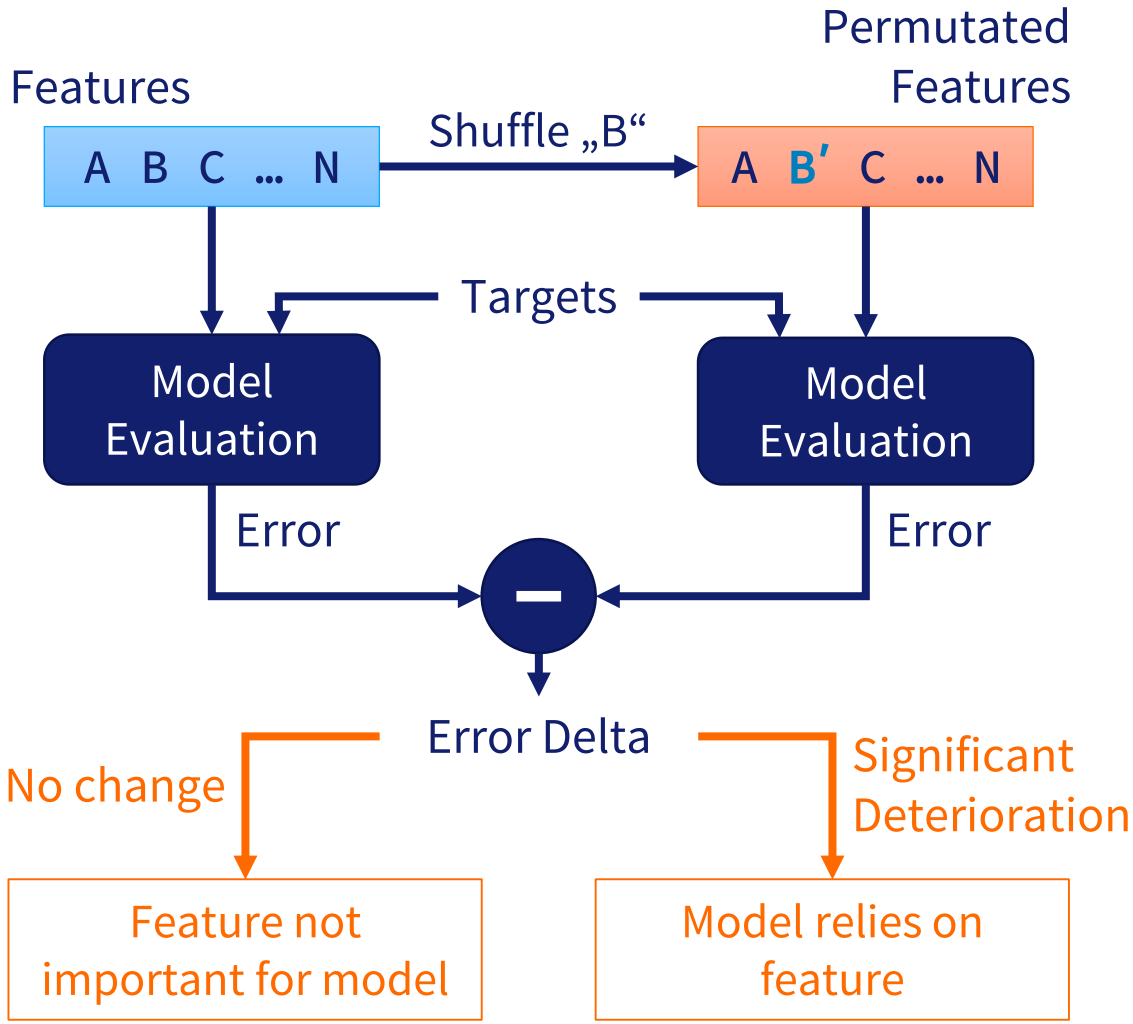
RMSL10E	Simple Features	Simple + Expert Features
RandomForest	0.297	0.292
SVR	0.333	0.324

5-fold cross-validation results

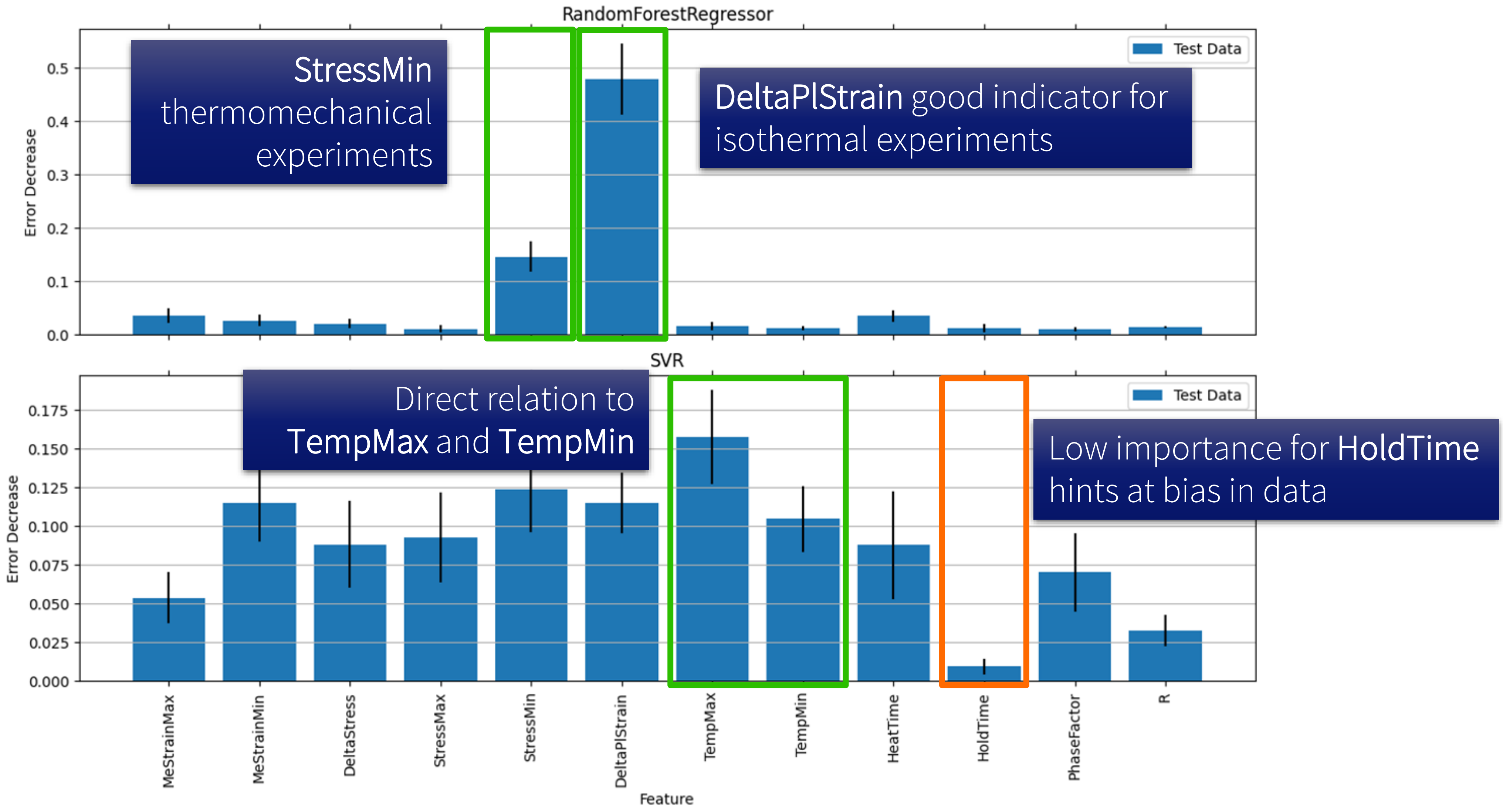
Expert model based on material properties from a subset of the data reached a RMSL10E of **0.496**.

XAI – Permutation Feature Importance (PFI)

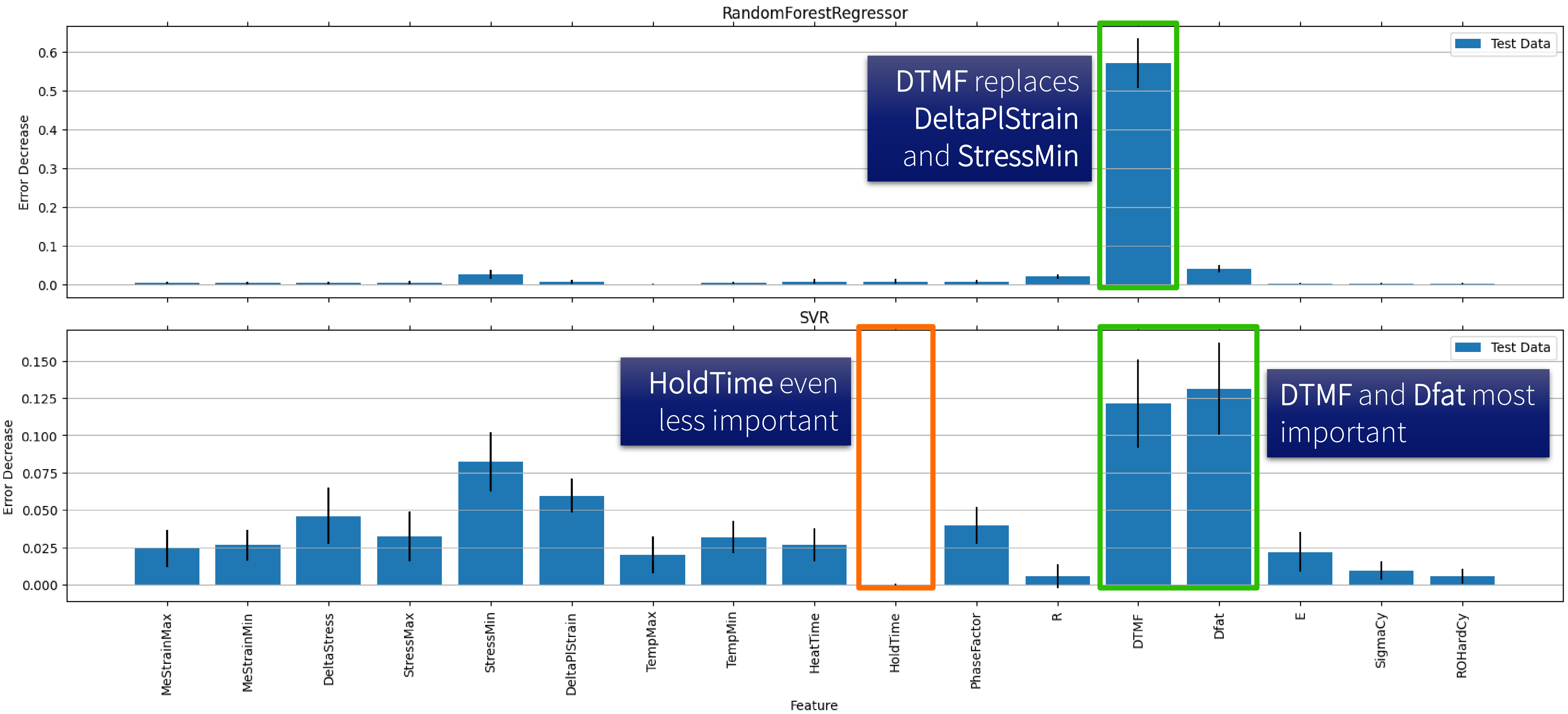
Randomly swap values of a feature and evaluate impact on model performance.



PFI – Simple Features



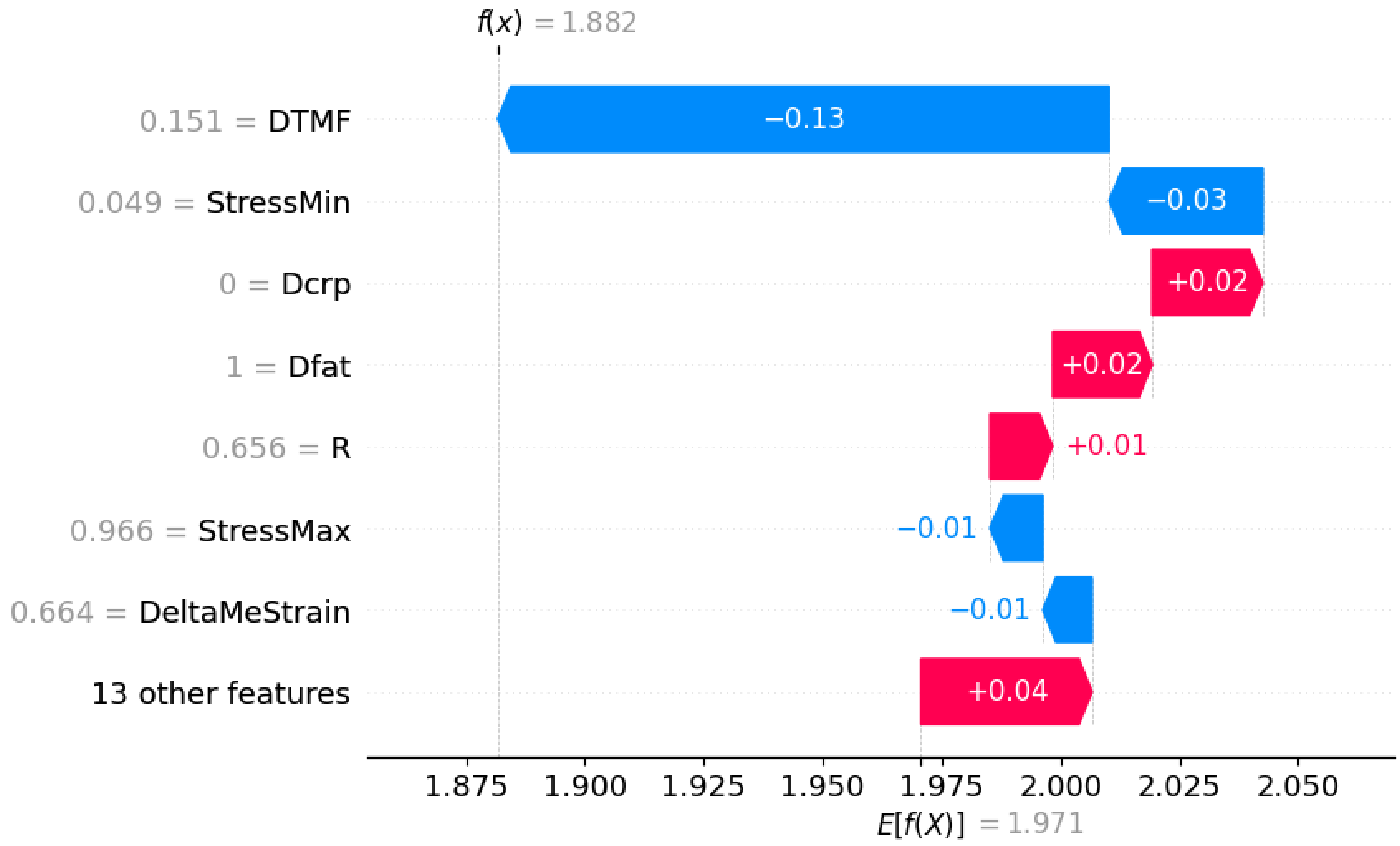
PFI – Simple + Expert Features



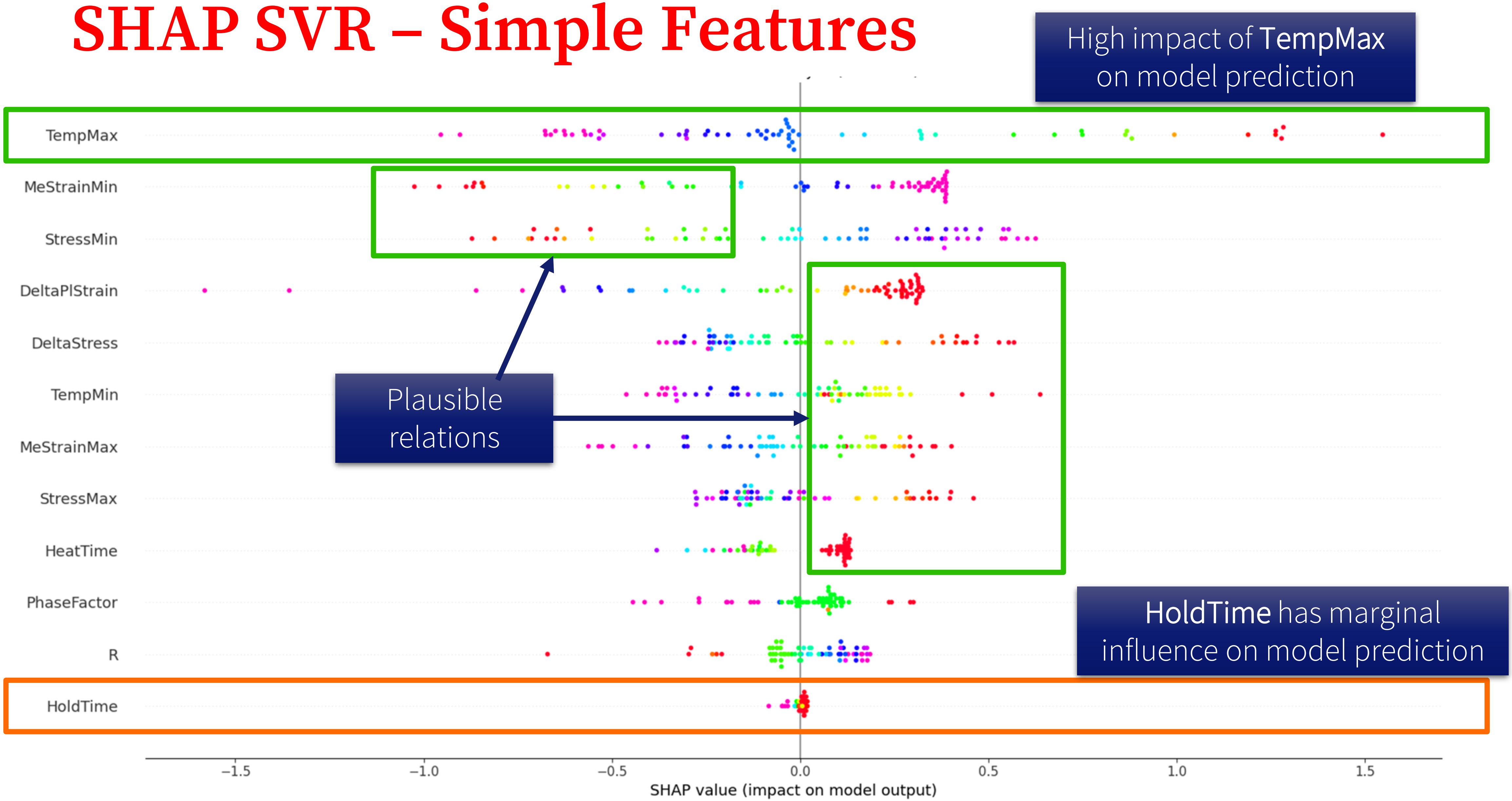
XAI – Shapley Additive Explanations (SHAP)

- SHAP value (ϕ) measures contribution of feature to the deviation from the expected value ($E[f(x)]$)
- Model Prediction as sum of expected and SHAP values:

$$f(x) = E[f(x)] + \sum_i \phi_i$$



SHAP SVR – Simple Features



Conclusion & Future Work

- XAI able to discover multiple plausible relations of domain
- Results indicate that certain features could be better represented by the expert model
  - However, not clear yet how
- ML model more susceptible to biases in dataset compared to expert model
  - Different data required for calibrating expert models and for training ML models

Future Work

- Boosting approach
  Use ML model to correct the expert model („Where is the expert model wrong?“)
  → better suited to discover potential improvements

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