

Exploring ICF Experimental Relationships Using Machine Learning

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Inertial Confinement Fusion (ICF)

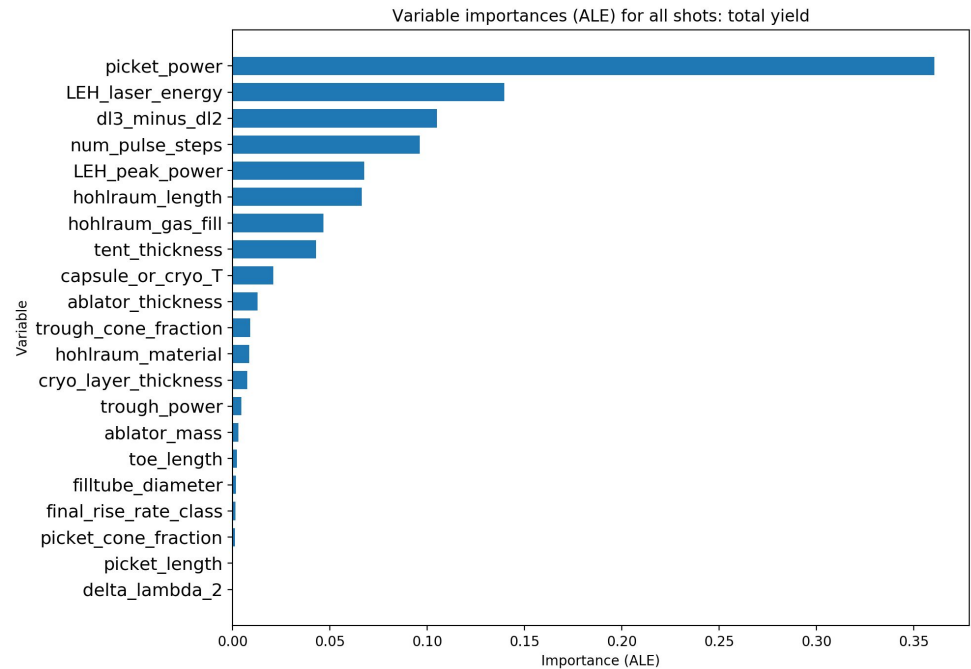
- Generates nuclear fusion reactions by heating and compressing a deuterium-tritium (DT) filled capsule
 - Indirect drive: lasers heat a cavity (hohlraum) containing the DT capsule
- Plasma ignition would yield many times the input energy
 - However, much of the underlying physics in ICF is not well understood
- Better understanding of what experimental results tell us about design parameters is necessary to inform simulations and guide future experiments

Our goal: leverage machine learning to better understand dominant physical mechanisms in ICF

- Random forest (RF) regression is an ensemble ML method that combines multiple decision trees to produce highly accurate predictions
 - Unlike neural nets, RFs don't require large datasets to produce accurate results
- Our work uses a random forest predictor to analyze sensitivity of experimental outputs to design inputs
 - Goal: identify novel and/or unexpected input-output relationships

We can identify design parameters strongly predictive of outputs using ML interpretability metrics

- ALE (Accumulated Local Effects)
- Model-agnostic global sensitivity metric
- Average variance in model predictions for a given range of each input feature (Apley & Zhu, 2019)
- Unbiased in presence of correlated features (unlike PDP)



We apply these techniques to data from 140 experiments conducted at NIF beginning in 2011

- Our model uses 21 design parameters to predict 4 output parameters
 - Outputs: total yield, velocity, ρR from dsr, gated X-ray bang time (BT)
- We use Bayesian ridge regression to estimate missing values as a function of other features
 - Poor choice of imputation method can skew model results
- We incorporate provided experimental uncertainties into our analysis
 - Physical origins not noted, but we treat each as one σ
 - We use $\sigma = \pm 15 \mu\text{m/ns}$ as velocity uncertainty

Major design changes over time

- Shift from high to low density hohlraum gas fills
- Data contains ~70 high density (Group I) and ~70 low density (Group II) shots
- We first analyze all 140 shots together, then analyze Groups I & II separately

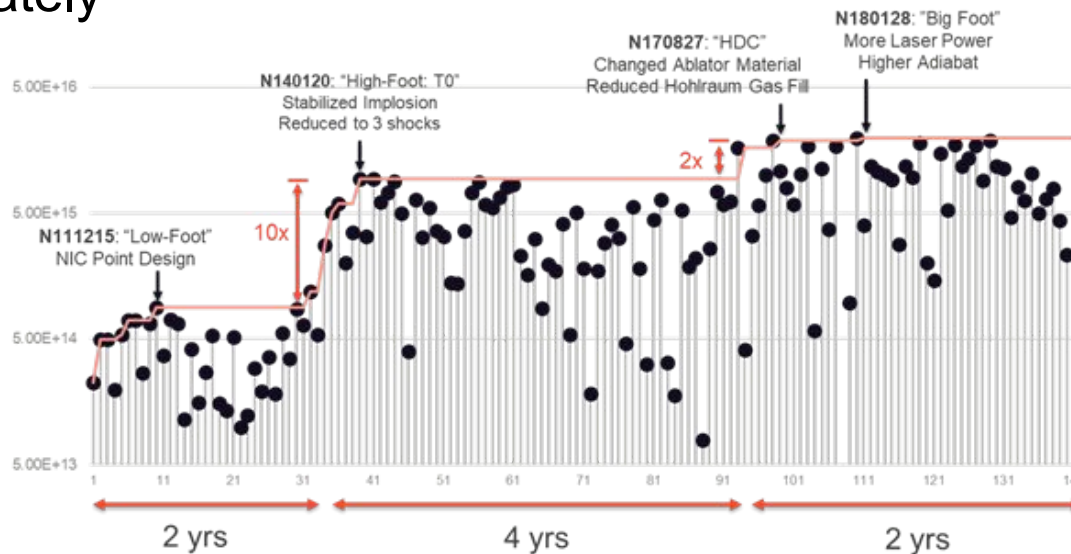
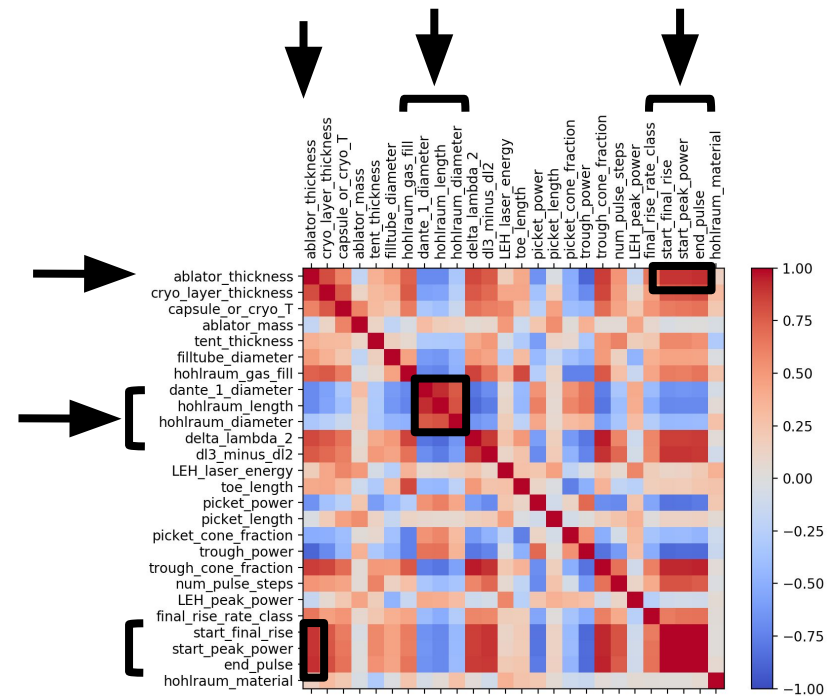


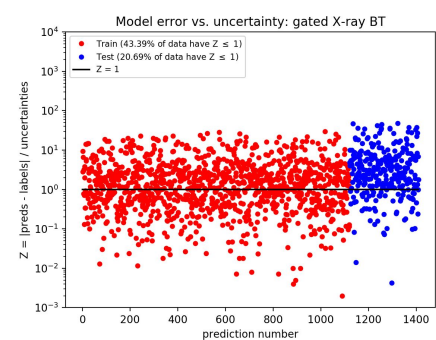
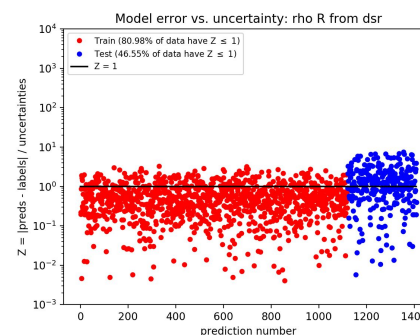
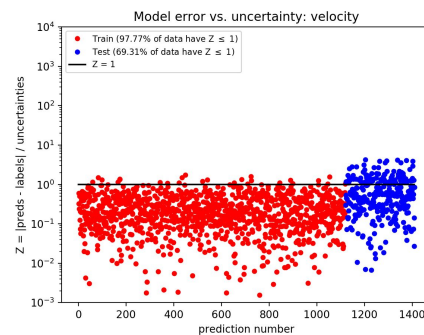
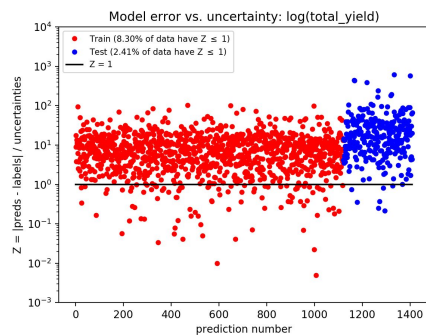
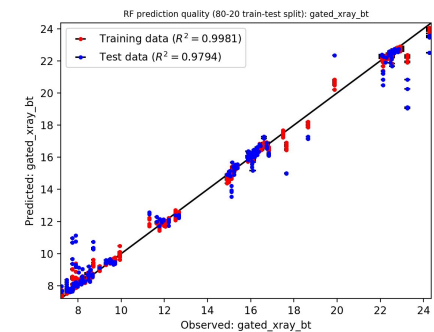
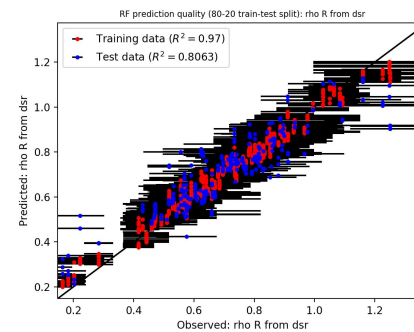
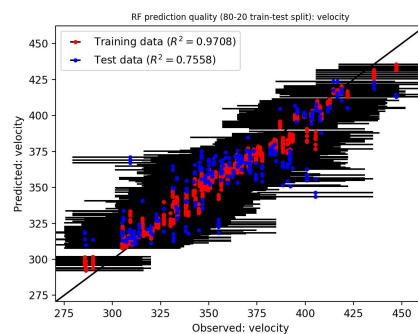
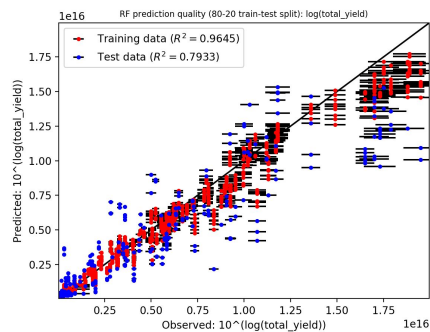
Image provided by Sean Finnegan (LANL)

Correlations between design inputs

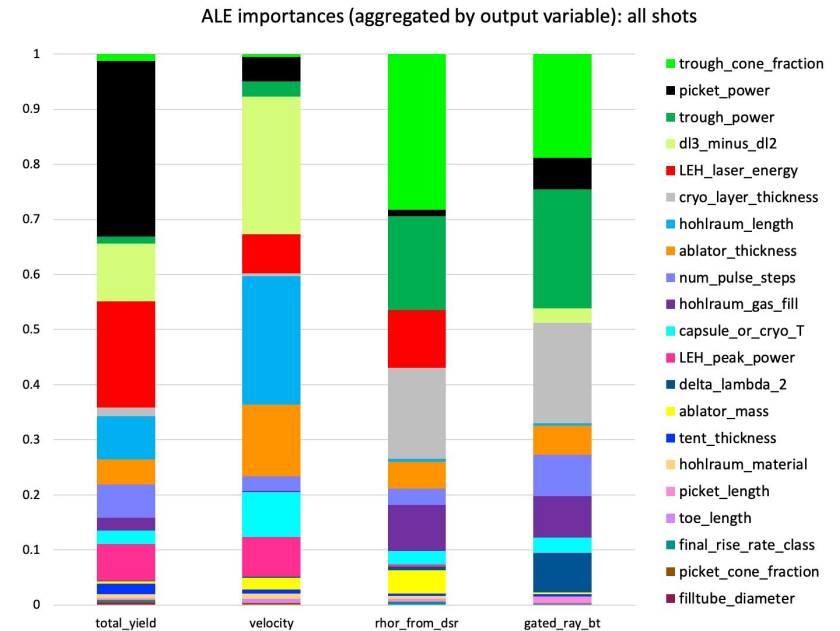
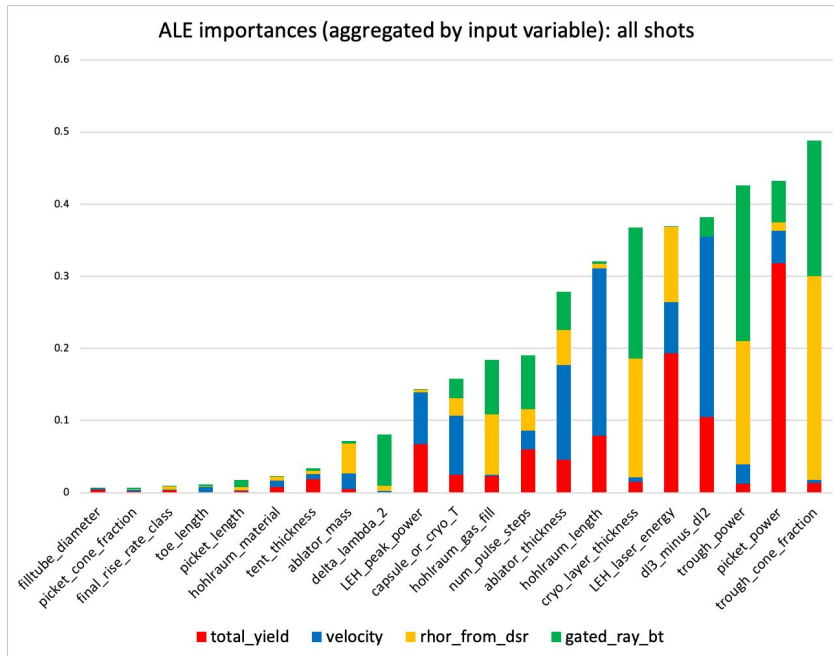
- Correlated features affect importance rankings
- Removed variables: start final rise, start peak power, end pulse, dante 1 diameter, hohlraum diameter
- Rigorous assessment of parameter correlations and relationships is reserved for future work (see Fernández-Godino)



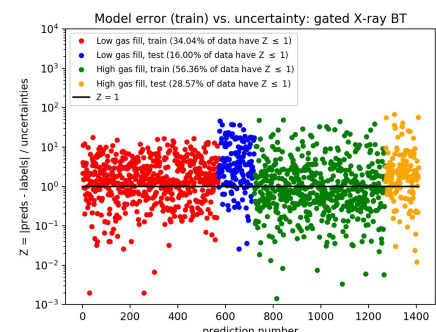
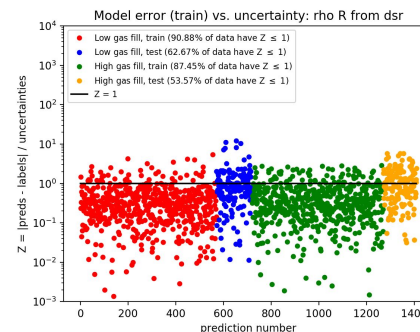
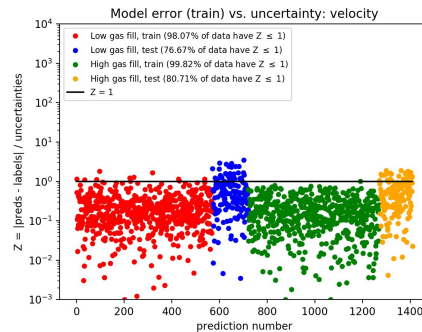
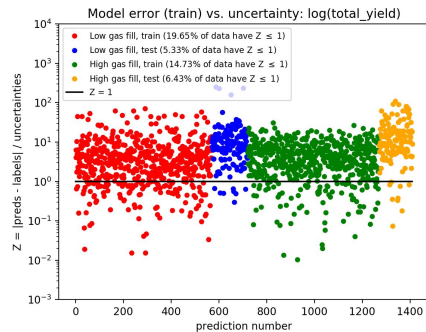
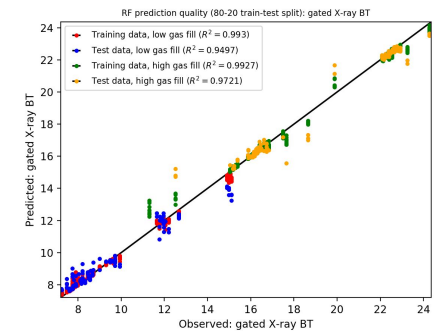
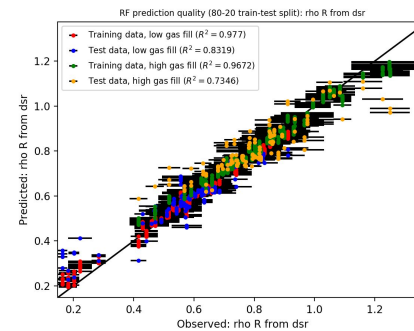
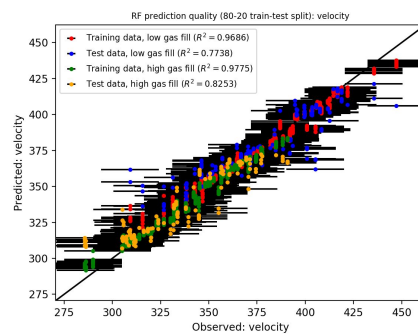
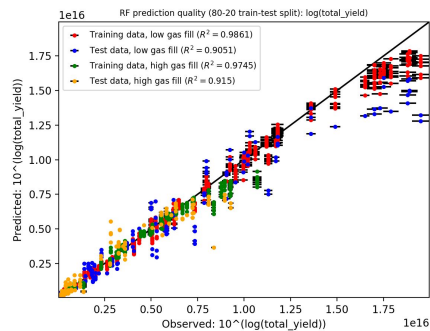
The random forest is a highly accurate predictor across outputs



ALE feature importance rankings

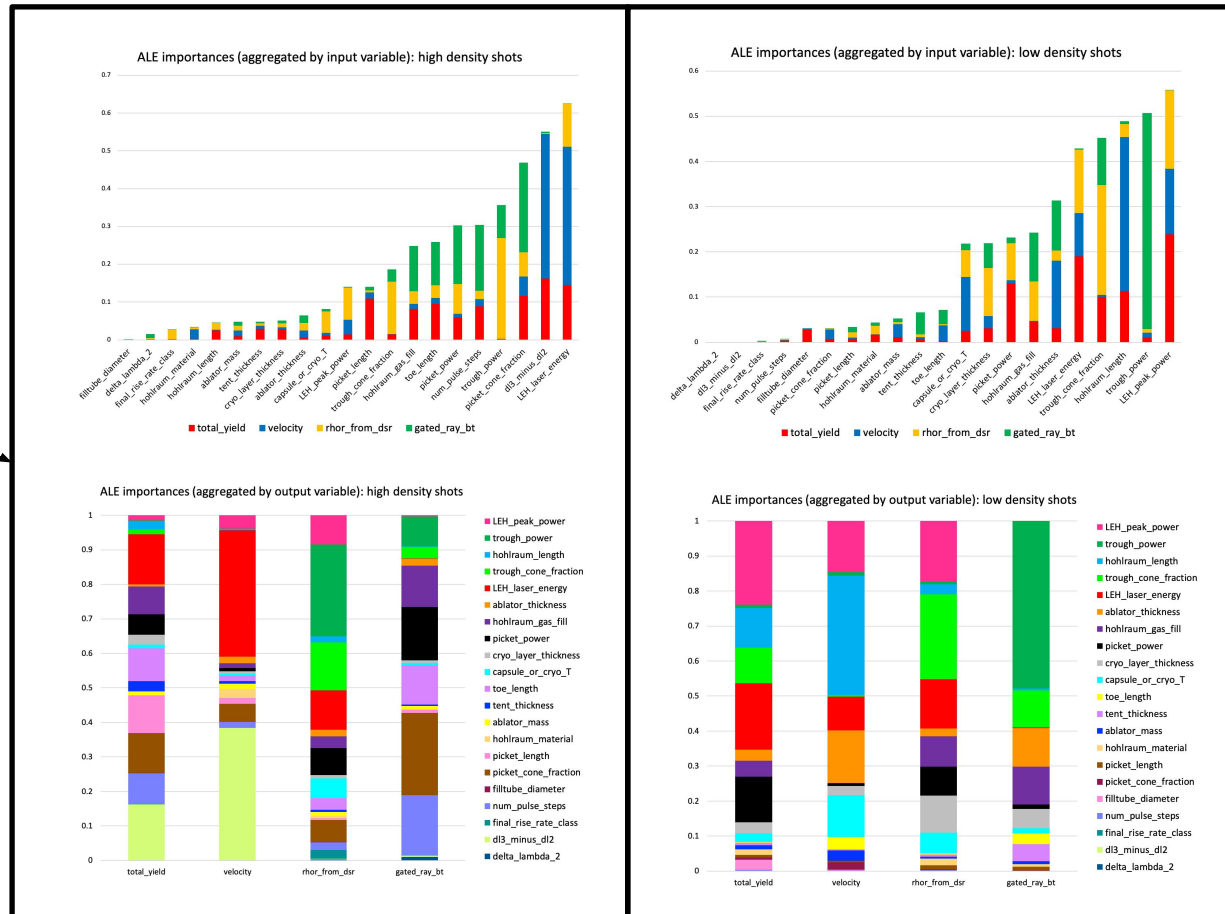


Predictions for groups I & II



Importance rankings differ significantly between groups, consistent with experimental design changes

High Gas Fill
(Group I)



Low Gas Fill
(Group II)

Summary

- Random forests are able to learn and predict on ICF experimental data with high accuracy
- The RF model is able to detect key experimental design changes, and ALE importance results are consistent with the effects of such design changes
- Feature importance results provide insight into relationships between design inputs and measurable outputs
 - These relationships can inform future ICF design

References

Apley, D. W., & Zhu, J. (2019). “Visualizing the Effects of Predictor Variables in Black Box Supervised Learning Models.” ArXiv:1612.08468 [Stat]. <http://arxiv.org/abs/1612.08468>

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