ICF Design Analysis Using Machine Learning

Julia B. Nakhleh, M. Giselle Fernández-Godino, Michael J. Grosskopf, Brandon M. Wilson, and Gowri Srinivasan

Slides: LA-UR-20-23664
Narration: LA-UR-20-23712

Inertial Confinement Fusion (ICF)

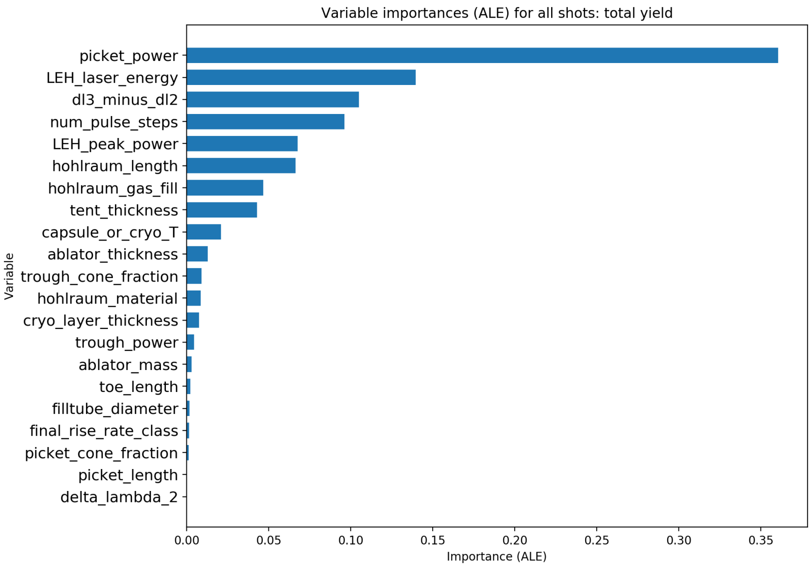
- Generates nuclear fusion reactions by heating and compressing a deuterium-tritium (DT) filled capsule
  - Indirect drive: lasers heat a cavity (hohlraum) containing the DT capsule
- Plasma ignition would yield many times the input energy
- However, much of the underlying physics in ICF is not well 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)

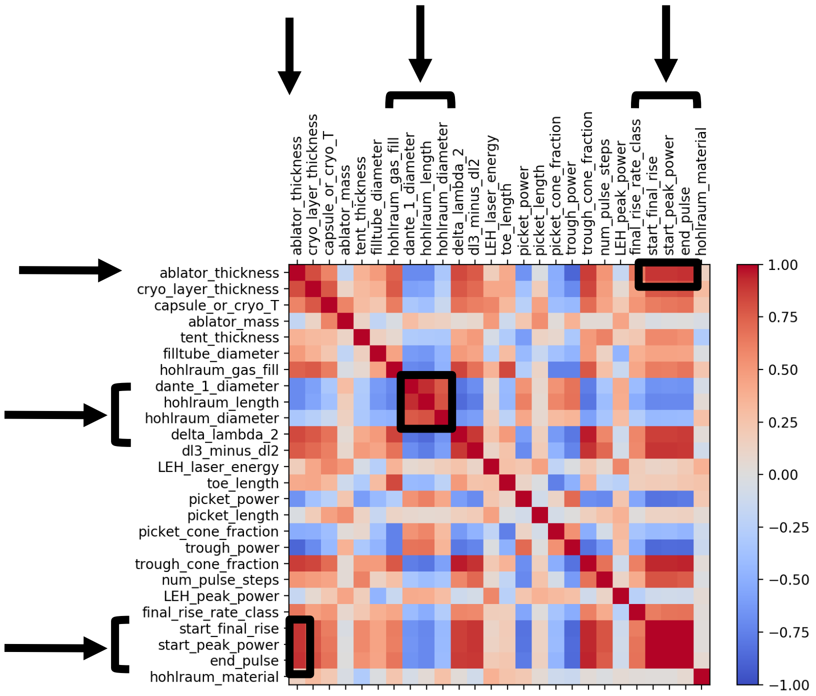


We will apply this to data from 140 experiments conducted at NIF beginning in 2011

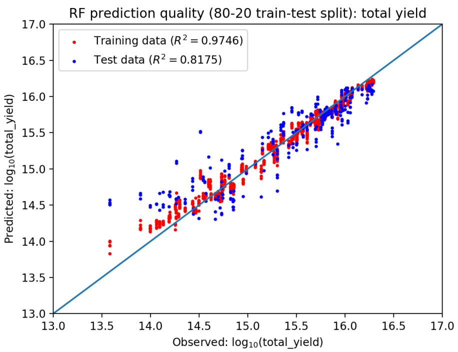
- Our model uses 21 design parameters to predict 5 output parameters
  – Outputs: total yield, velocity, neutron yield, ρR from dsr, and gated X-ray BT
- Shift from high to low density hohlraum gas fills
  – Data contains ~70 high density (Group I) and ~70 low density (Group II) shots
  – We first analyze all 140 shots together, than analyze Groups I & II independently
- We used Bayesian ridge regression to estimate missing values as a function of other features (iterative imputation)
  – Poor choice of imputation method can skew model results

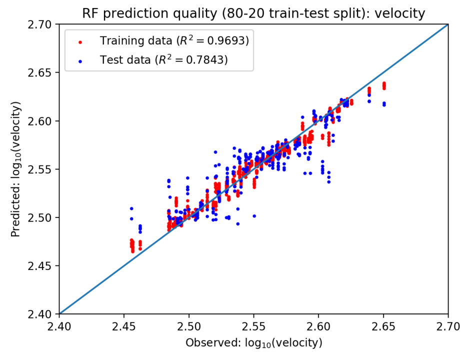
Correlations Between Design Inputs

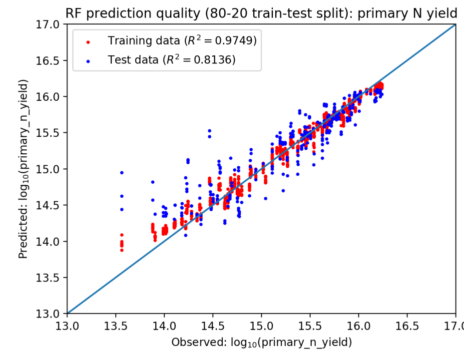
- Correlated features affect importance rankings
- Removed variables: start final rise, start peak power, end pulse, dante 1 diameter, hohlraum diameter
- Rigorous assessment of parameter correlations and relationships is reserved for future work (see Fernández-Godino)

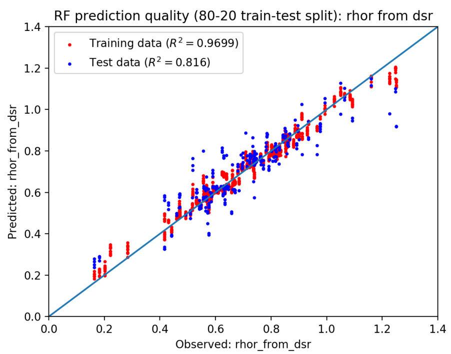


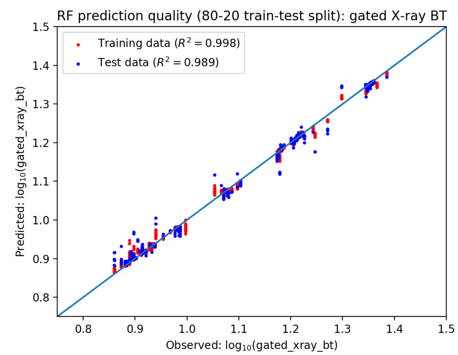
The random forest is a highly accurate predictor across outputs



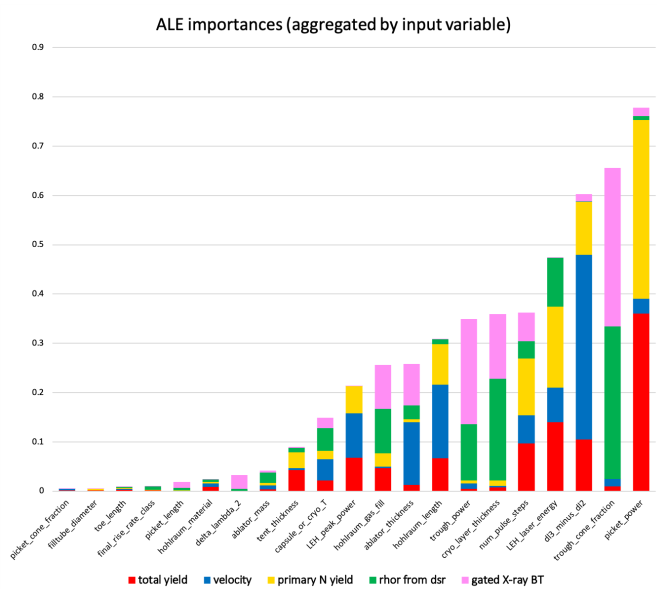


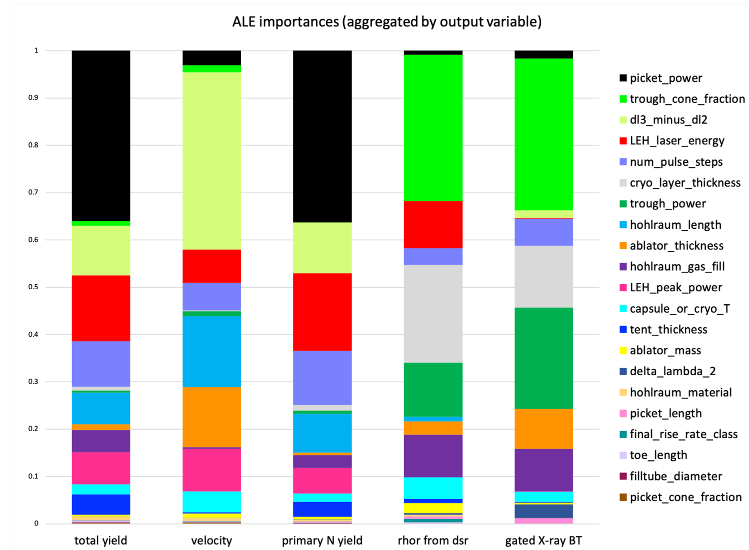




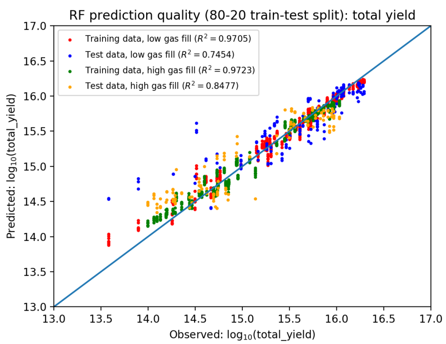


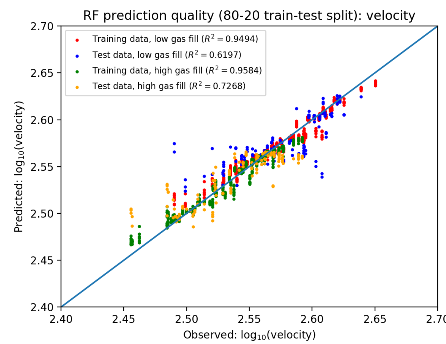
Importance analysis across inputs/outputs

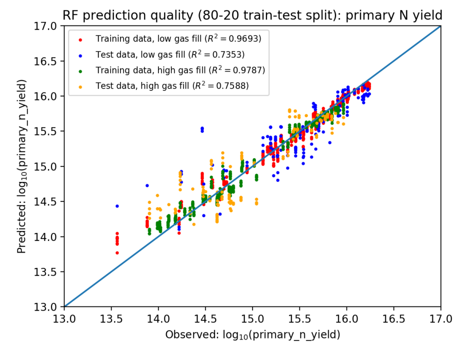


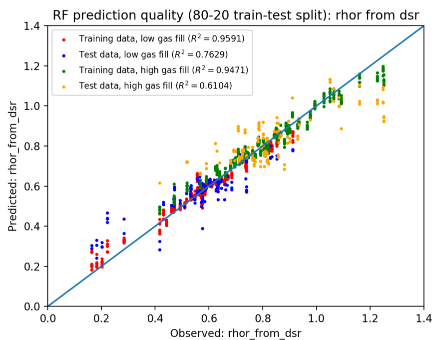


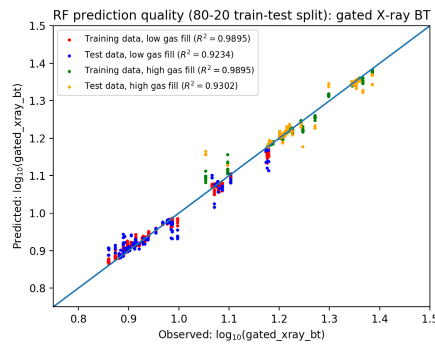
Experiments can be split into high and low gas fill – We can fit the prediction model separately to capture different physical relationships





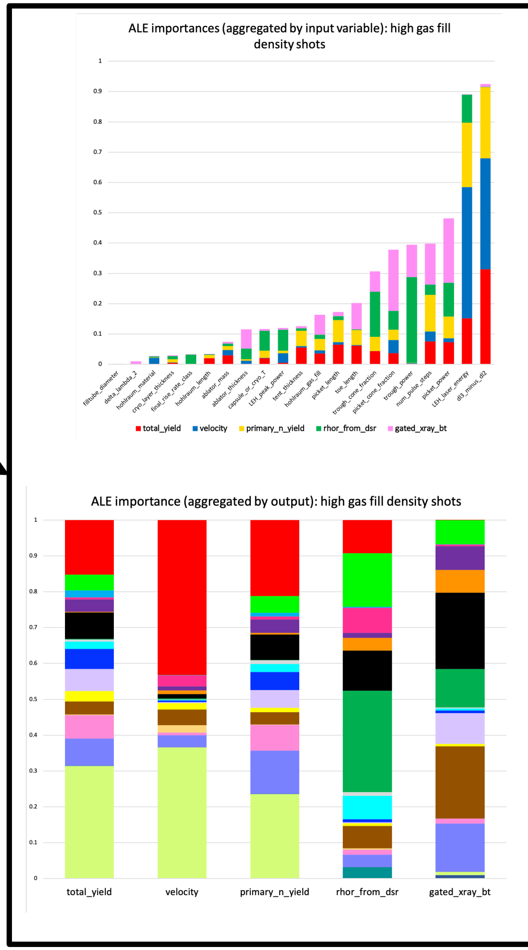


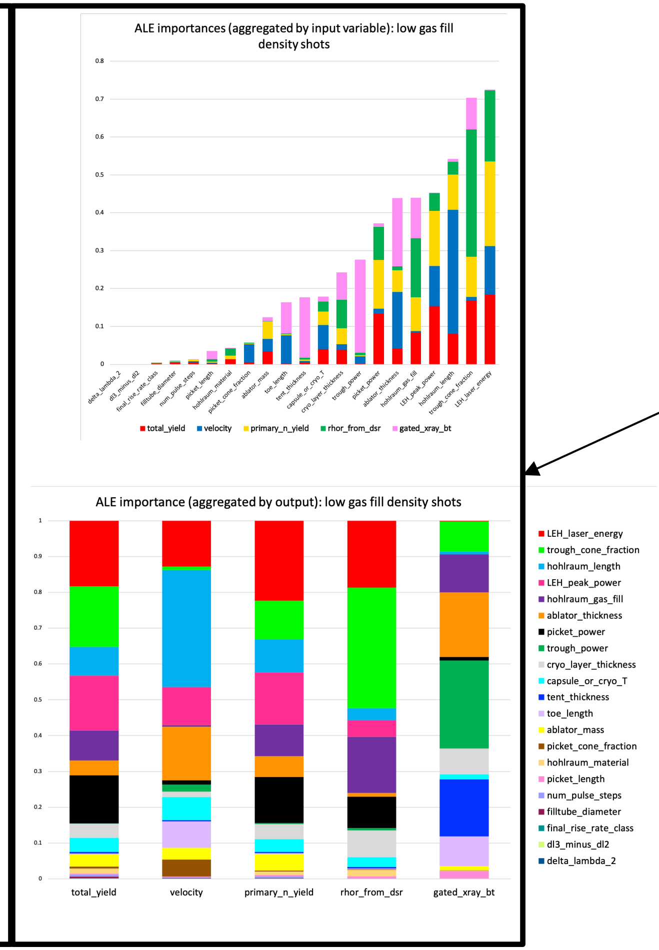




Importance rankings differ significantly between high and low density shots

High Gas Fill
(Group I)





Low Gas Fill
(Group II)

Future Work

- PCA and Sparse PCA (see talk by Fernández-Godino)
  - Identify groups of correlated input variables and assess physical relationships/meaningfulness of groupings
  - Use identified groupings to inform RF and improve model performance
- Analysis of relationships with discrepancy
  - Use RF to analyze discrepancy between simulation predictions and experimental results
  - Identify the extent to which different inputs affect discrepancy

Summary

- ML provides a novel method of ICF analysis
- Random forests are able to learn and predict on experimental data with high accuracy
- 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