

Machine Learning Analysis on the JET Pedestal Database

or how I learned to worry about high n_e^{ped}

9 June, 2021

Overview

JET Pedestal Database

Machine Learning

Conclusion

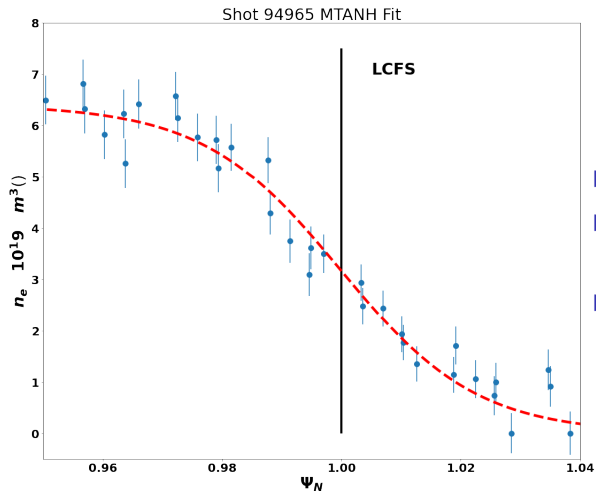
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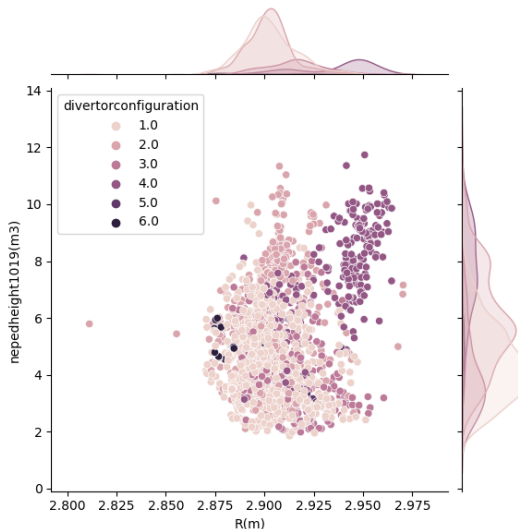
JET Pedestal Database



- ▶ H-Mode
- ▶ 75-95% ELM Cycle
- ▶ Focus on n_e^{ped} height

Input Parameters and Filtering

Eng. Param	Domain
I_P [MA]	[0.81, 4.48]
B_T [MW]	[0.97, 3.68]
a [m]	[0.83, 0.97]
R [m]	[2.8, 2.975]
δ [-]	[0.16, 0.48]
M_{eff} [-]	[1.0, 2.18]
P_{NBI} [MW]	$[10^{-3}, 32.34]$
P_{ICRH} [MW]	[0, 7.96]
P_{TOT} [MW]	[3.4, 38.22]
V_P [m ³]	[58.3, 82.19]
q_{95} [-]	[2.42, 6.04]
Γ [10^{22} e/s]	[0, 15.5]
H [-]	[0, 0.18]
Γ_{SD} [10^{22} e/s]	[0, 1000]
DC [-]	[VV ...]



- ▶ Shafranov Shift → remove R
- ▶ Γ_{SD} varies too much.
- ▶ Only numerical
- ▶ Only Deuterium
- ▶ No RMPs, Kicks, or Pellets
- ▶ HRTS Validated

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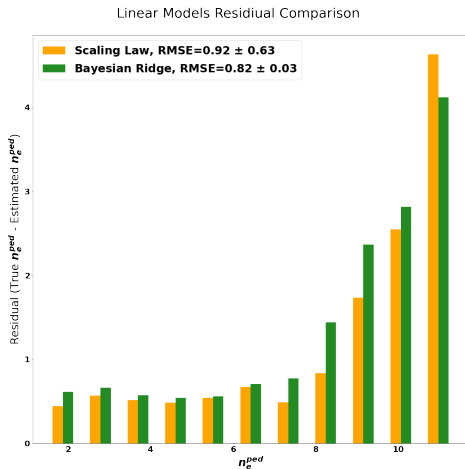
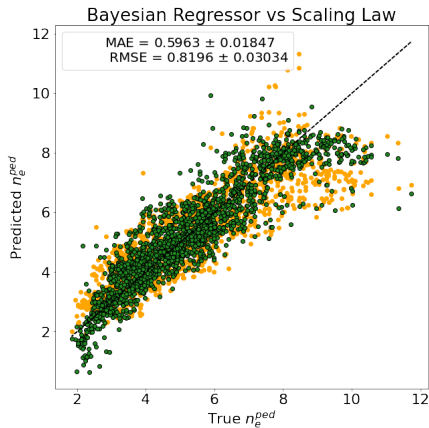
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Linear Regression



$$n_e^{ped} = (9.9 \pm 0.3) I_p^{1.24 \pm 0.19} P_{TOT}^{-0.34 \pm 0.11} \delta^{0.62 \pm 0.14} \Gamma^{0.08 \pm 0.04} M_{eff}^{0.2 \pm 0.2} \quad (1)$$

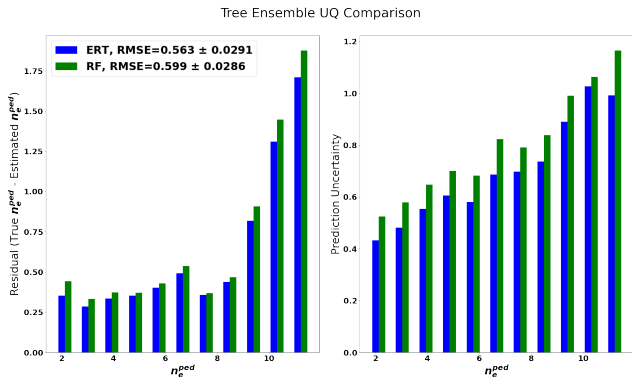
Linear Regression

- ▶ Achieve better RMSE using all inputs
- ▶ But lose interpretability →
- ▶ Prediction uncertainty normally distributed between 1.6 - 1.8

Feature	μ	σ^2
I_p	0.15	0.06
B_T	0.956	0.072
a	2.966	0.479
δ	12.95	0.154
V_P	-0.05	0.007
q_{95}	-1.064	0.0542
P_{NBI}	-1.911	0.0546
P_{ICRH}	-1.976	0.0561
P_{TOT}	1.926	0.0557
Γ	0.125	0.007
H	-4.016	0.374
M_{eff}	1.369	0.053

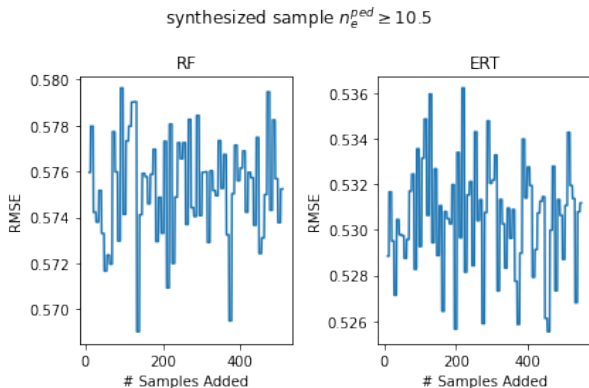
Random Forests & Extreme Randomized Trees

- Uncert. covers residual



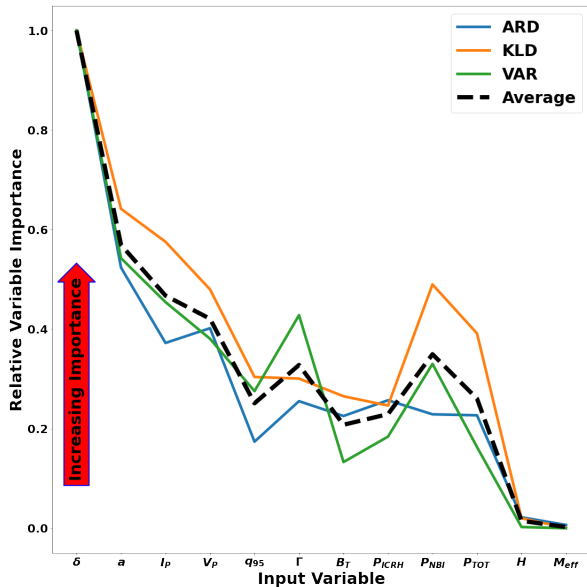
Random Forests & Extreme Randomized Trees

- ▶ Uncert. covers residual
- ▶ Meta-modeling
→ no effect



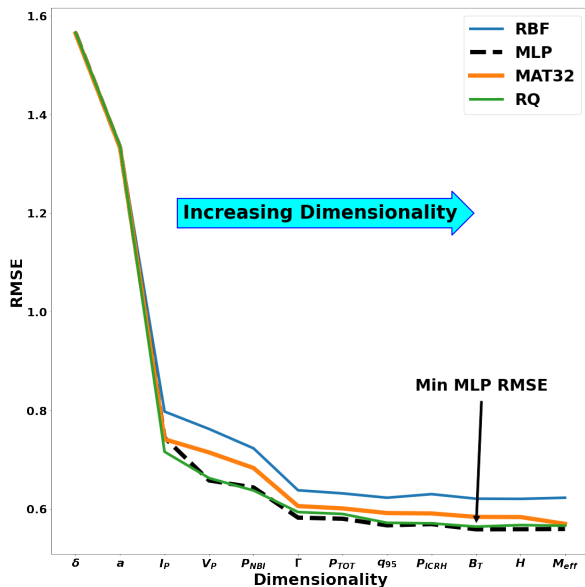
Gaussian Processes

► Sensitivity Analysis



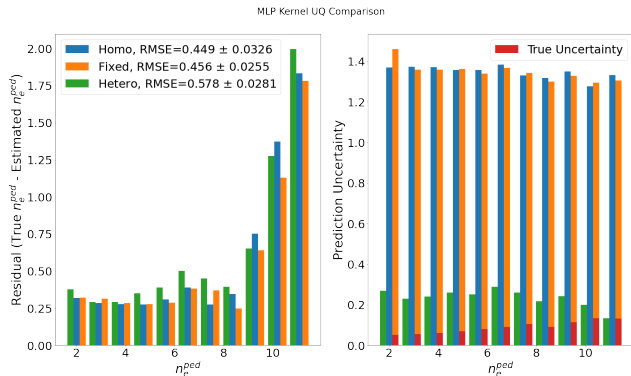
Gaussian Processes

► Sensitivity Analysis



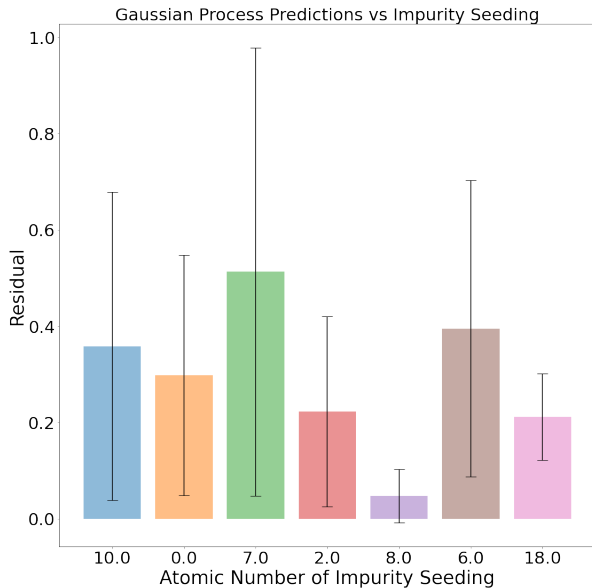
Gaussian Processes

- Sensitivity Analysis
- UQ



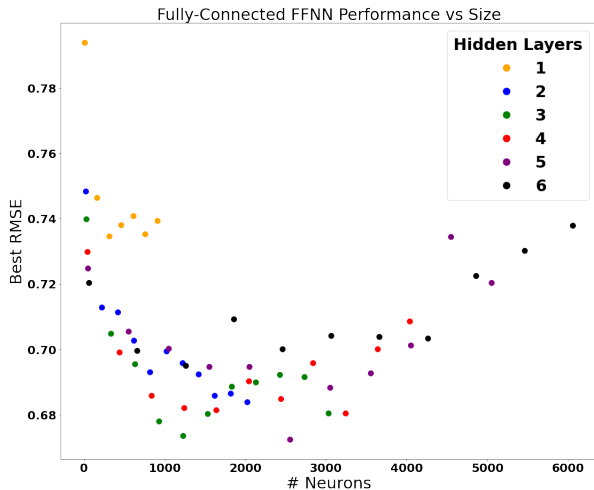
Gaussian Processes

- Sensitivity Analysis
- UQ
- Impurity seeding



ANNs

► Crawling



ANNs

- Crawling
- Ensembling

ANN Ensembles UQ Comparison

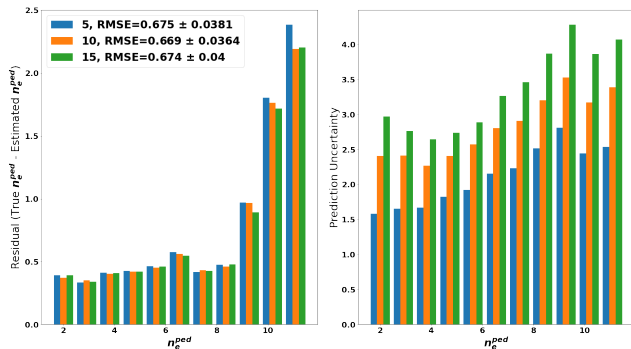


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- ▶ Non-linear models outperform linear models
- ▶ RFs and ERTs work well as black box models
- ▶ Heteroscedastic GPs can map latent uncertainty
- ▶ Shallow ANNs perform best

Future Work

- ▶ Fit models on varied subsets of database
e.g., compare how linear coefficients vary when trained on $q_{95} \leq 3.0$ versus $q_{95} > 3.0$.
- ▶ UQ of main engineering parameters
- ▶ Ideas?