

ML-based acceleration of CAKE for real-time kinetic equilibrium reconstruction

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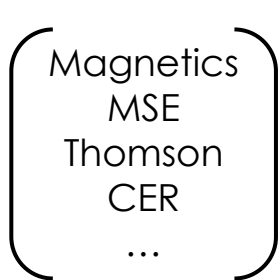
Outline

- Introduction
- NN training
- Training results
- Summary & Future works

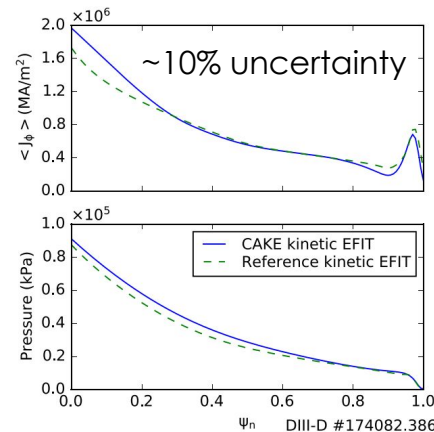
Introduction

[1] Z Xing et al, Fus. Eng. Des. 163 (2021) 112163

- **CAKE (Consistent Automatic Kinetic Equilibrium reconstruction) [1]**



Filtering channels
Constraints
NUBEAM/ONETWO
EFIT iteration



(CAKE02)



Automated
Consistent
Robust



Many iteration
Costly computation (Not RT feasible)



**Real-time kinetic EFIT is now ready by using neural net
acceleration (CAKE-NN)**

Neural network architecture for CAKE-NN

Inputs

Scalars

(Bt, Ip)

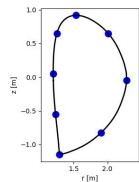
MSE

pitch angles
(1-11, 41-44)

$(Y_1, Y_2, \dots, Y_{11}, Y_{41}, Y_{42}, \dots, Y_{44})$

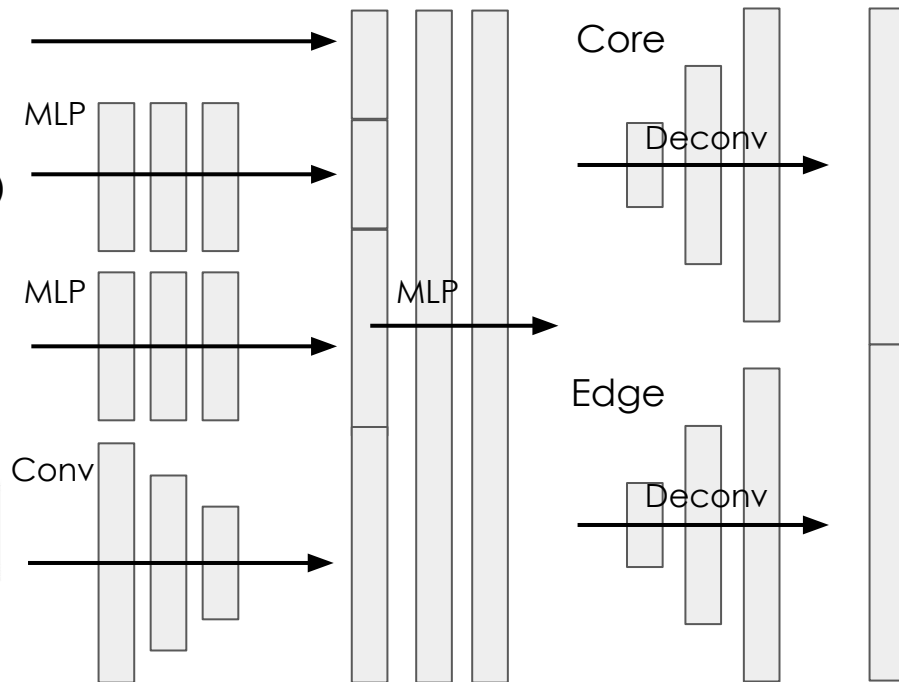
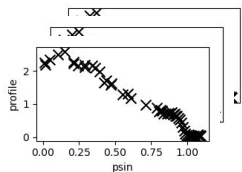
Boundary

8 * (r, z) from
RT-EFIT



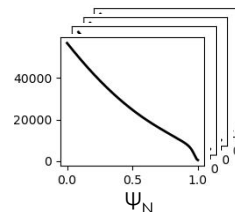
Measured profile signals

Thomson, CER,
p & q from RT-EFIT



Outputs

p, j, q, ne, Te, Ti, rot

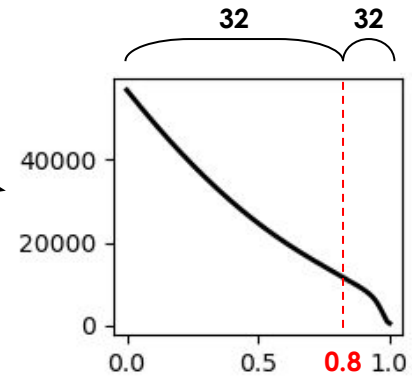


“Multimodal neural network”

Training data collection

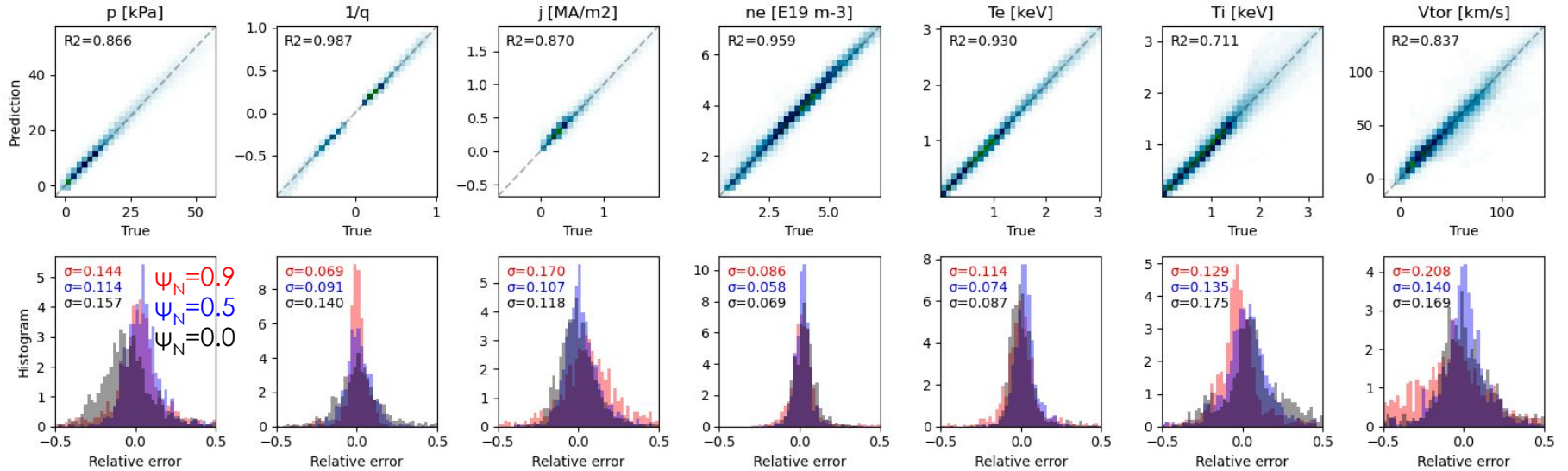
- Shots: 178000 - 192000 in DIII-D (MSE, Thomson, CER available)
 - Interval: 100 ms averaged
 - Prediction outputs: $\rho(\psi_N)$, $1/q(\psi_N)$, $j(\psi_N)$, $n_e(\psi_N)$, $T_e(\psi_N)$, $T_i(\psi_N)$, $V_{\text{tor}}(\psi_N)$
 - Spatial resolution: 32 for core & 32 for edge
-
- ~10000 samples after filtering outliers
 - Train:Validation:Test = 7:2:1

To avoid diverging at the boundary



Training results of CAKE-NN

- Regression for test dataset: Good!

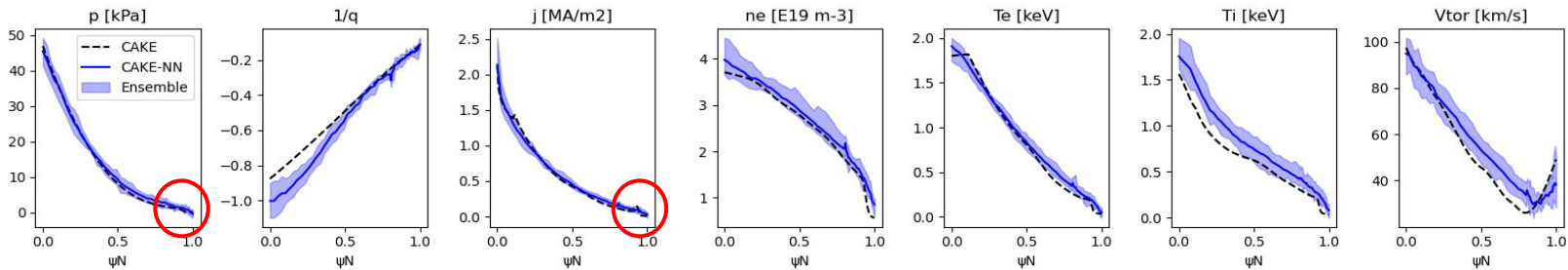


- The error of CAKE-NN is ~10%, which is the same level as the uncertainty of CAKE.
- CAKE-NN has similar reliability to CAKE, but much faster than that (**real-time feasible!**).

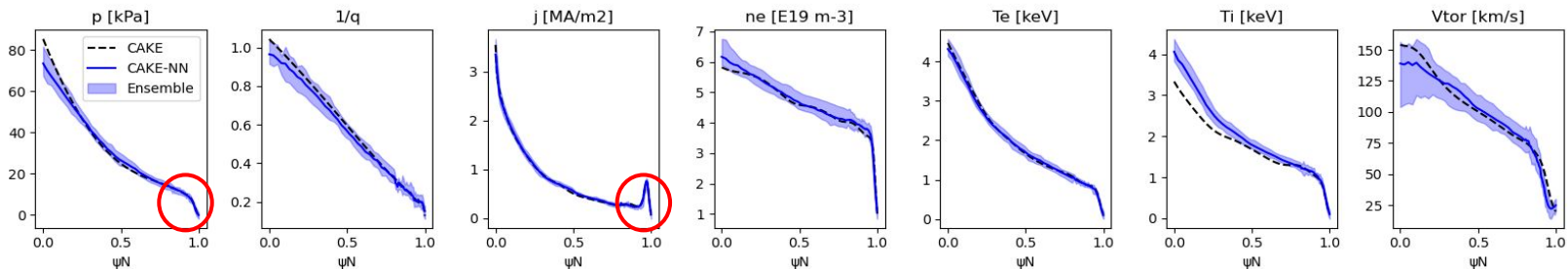
Training results of CAKE-NN

- Prediction examples: Capturing physics patterns

L-mode
190919_4800



H-mode
191005_5000

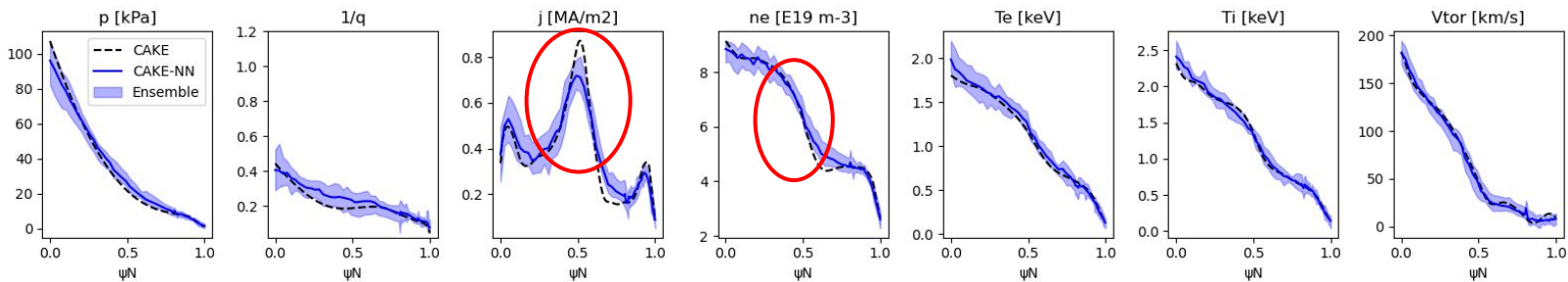


- CAKE-NN successfully captures different physics patterns such as the pedestal structure and bootstrap current in L- and H-mode plasmas.

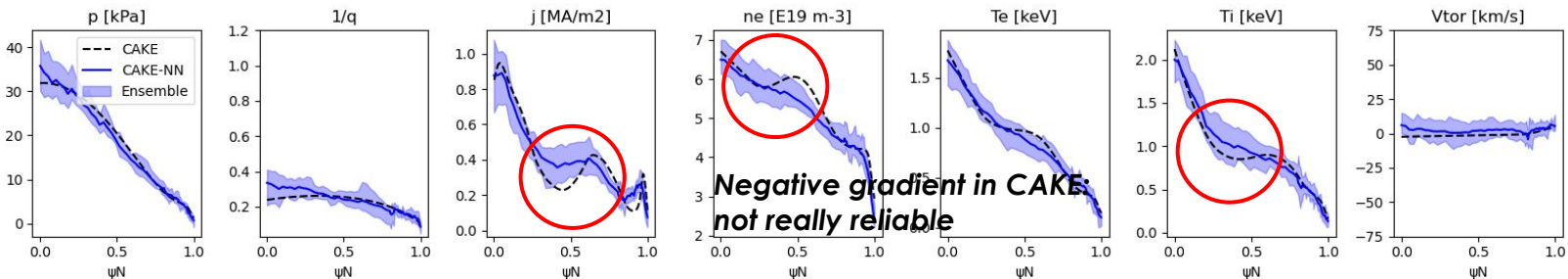
Training results of CAKE-NN

- **Prediction examples: Robustness in extreme cases**

Strong ITB
190895_3600



Better than
CAKE
190899_4900



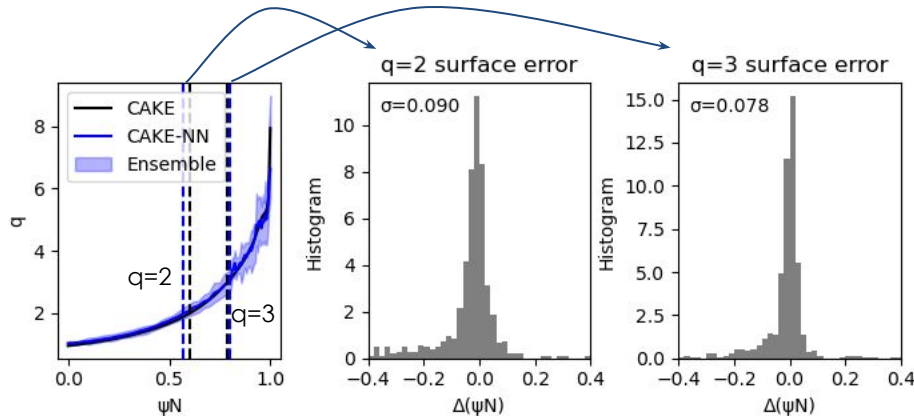
- CAKE is an automated system, so there can be unreliable results when measurements are noisy or missing.
- CAKE-NN shows more reasonable predictions for noisy inputs -> **More robust for real-time implementation.**
- But CAKE-NN shows quite jagged profiles for extreme cases: post-processing needed.

Training results of CAKE-NN

- **Physical reliability**

- Real-time prediction and control using CAKE-NN requires enough reliability to estimate physical information (ex. q=2 surface, pedestal height).

1. Estimation of (q = 2 and 3) surface



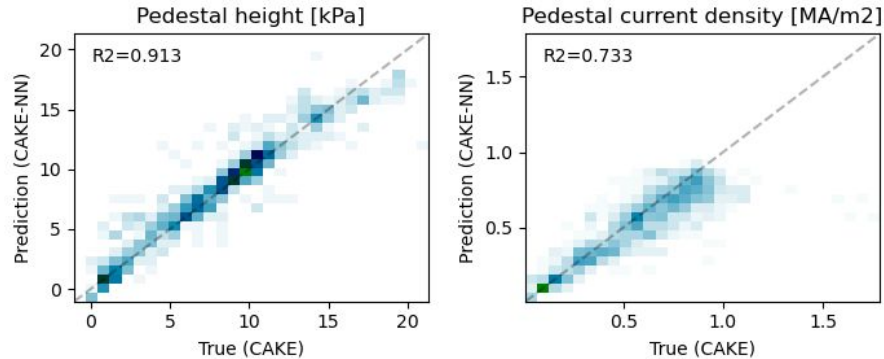
- Good ($\Delta(\psi_N) < 0.1$).

Training results of CAKE-NN

- **Physical reliability**

- Real-time prediction and control using CAKE-NN requires enough reliability to estimate physical information (ex. $q=2$ surface, pedestal height).

2. Estimation of pedestal information



- Pedestal height prediction is good.
- Pedestal current density prediction needs further improvement.

Summary & Future works

- **Summary**

- The NN acceleration of CAKE has been done for real-time implementation.
- CAKE-NN showed reasonable prediction accuracy for various cases.

- **Future works**

- Further optimization will be done (NN architecture, spatial resolution, ...) to improve the accuracy.
- Post-processing should be considered for the output profiles.
- PCS implementation on DIII-D will be done (**~ 1 month**).

- Possible applications: $q=2$ surface control, profile control, RT pedestal estimation, RT stability analysis

Thank you!

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