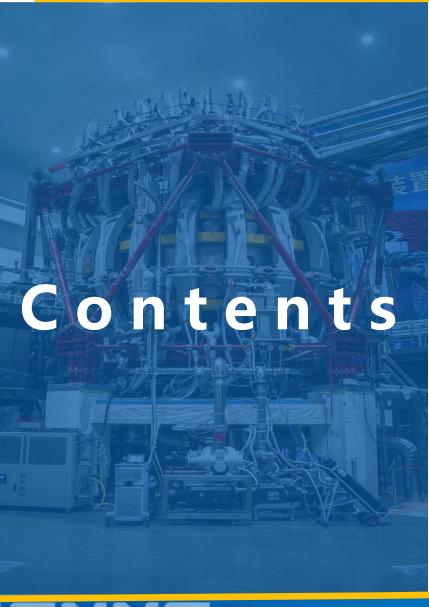


A Neural Network Model for Rapid Analysis and Extrapolation in Spectral Diagnostics

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Southwestern Institute of Physics
2 Tsinghua University



1. Background and motivations

- 2. Dataset and architecture
- 3. Results
- 4. Cross-device Study
- 5. Summary



Significance of real-time measurement

■ Essential for Future Reactors

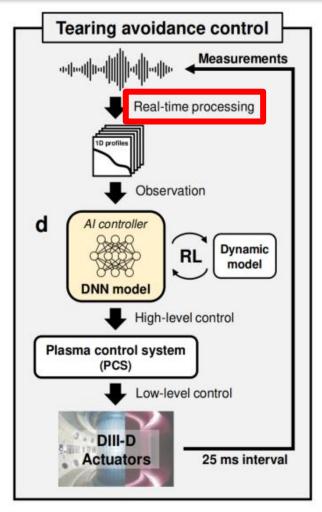
Real-time plasma control is essential for the operation of future fusion reactors.

■ Key Physics Parameters

Ion temperature (T_i) and rotation velocity (v_t) are among the most critical parameters.

■ The Bottleneck

Roles of T_i and v_t have been missing in most real-time control scenarios.



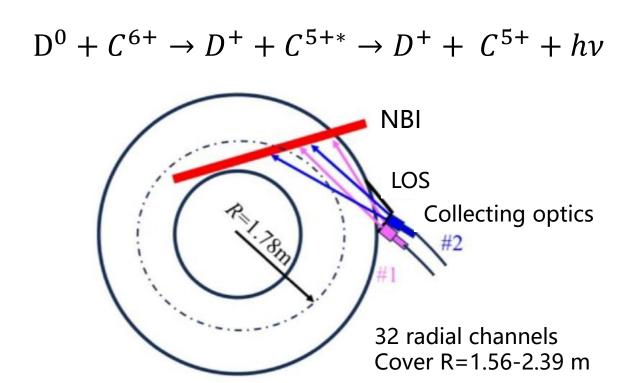
Real-time measurement of plasma parameters is the input for the control loop

Jaemin Seo et al. Nature (2023):626.

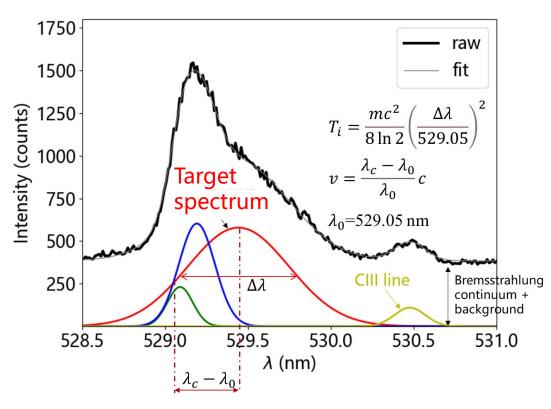
CXRS diagnostic on HL-3

Primary Diagnostic : Charge Exchange Recombination Spectroscopy (CXRS)

CXRS diagnostic measures light (hv) emitted by ionized impurities (e.g., C^{6+}) following charge exchange with neutral beam atoms.

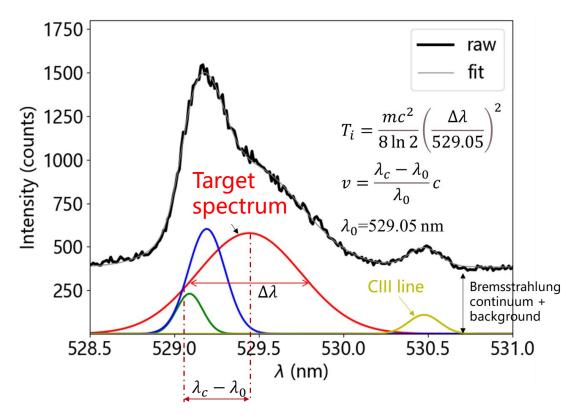


Schematic of CXRS diagnostic on HL-3 tokamak



Example of the collected CXRS spectra

Limitations of Conventional Spectral Analysis



Example of the collected CXRS spectra and its fit results

Non-linear Least-Squares Fitting

$$I(\lambda) = I_0 + \sum_{i=1}^{N} a_i \exp\left(-\frac{(\lambda - \lambda_i)^2}{2\sigma_i^2}\right)$$
$$E = \sum_{j=1}^{M} \frac{\left(I(\lambda) - y_j\right)^2}{\sigma_j^2}$$

High Computational Latency

~ 100 - 1000 ms per spectrum

1 Dependence on Expert Knowledge

Requires accurate initial guesses for parameters

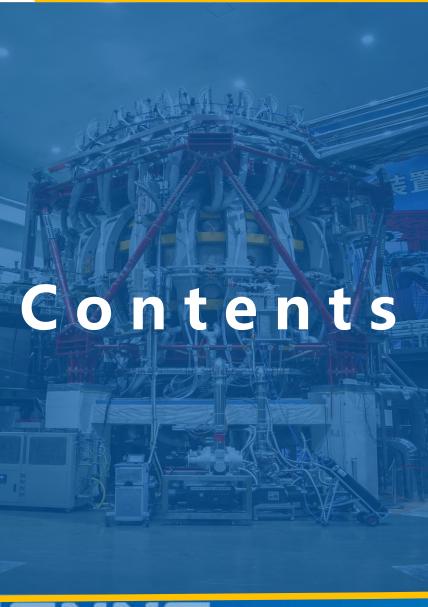


Our solution: Neural network spectrum analysis





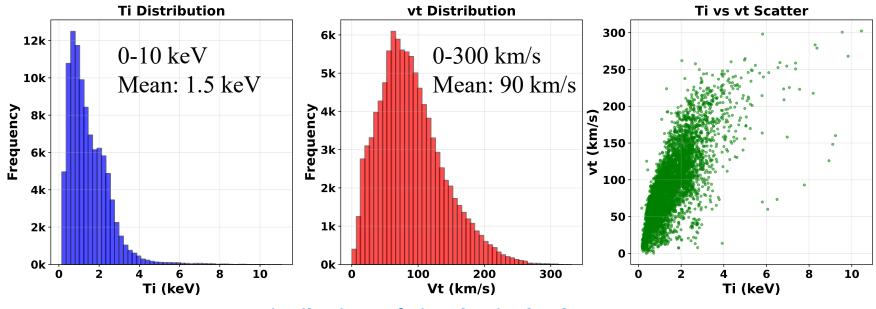
- Explore the feasibility of using NNs for rapid spectral analysis
- Explore Interpretability of the 'black-box' model: attribution analysis
- For application in future devices: cross-device investigation (HL-2A and HL-3 tokamaks)



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Dataset

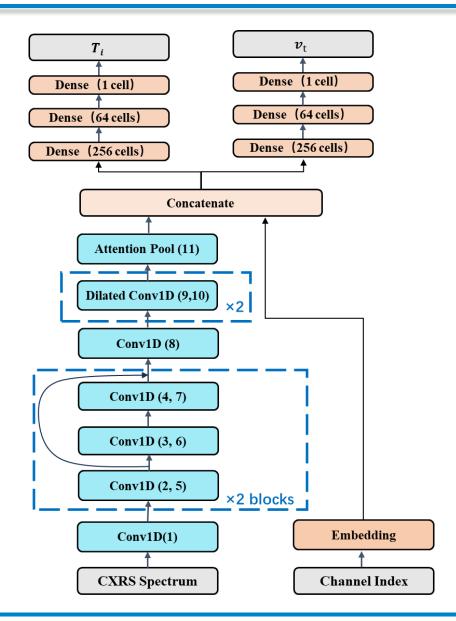
- Input: spectrum (1×200) , channel index (1×1)
- Output (label): T_i and v_t (1×1, 1×1) from Least-Squares Fitting
- Size: >100k spectra from 190 discharges on HL-3 tokamak
- Splitting rule: 5-fold cross validation. Stratified by shot number



Distributions of Ti and vt in the dataset



Architecture of model



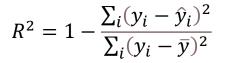
CNN backbone: For extracting localized, structured features from spectral signals.

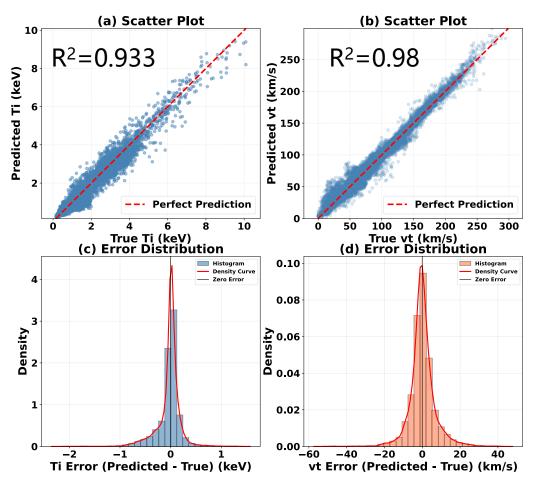
Channel embedding: Provides spatial awareness by encoding the channel/position index.

Attention pooling: Replaces global pooling to adaptively focus on critical spectral regions.

Multi-task learning: Shares representations to jointly predict T_i and v_t efficiently.

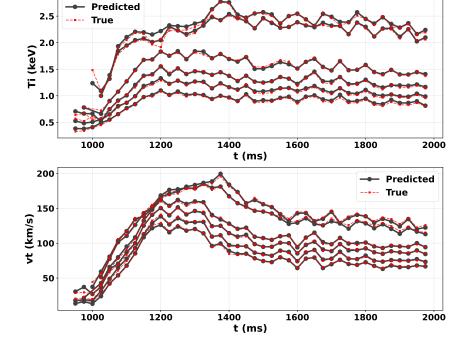






Parameter	R ²	MAE	MRE	Inference time
Ti	0.933	0.14keV	9.8%	0.56 ms/ 32 channels
vt	0.980	4.50km/s		

Shot 12541



- Achieves real-time capability
- **✓** High fidelity across time evolution

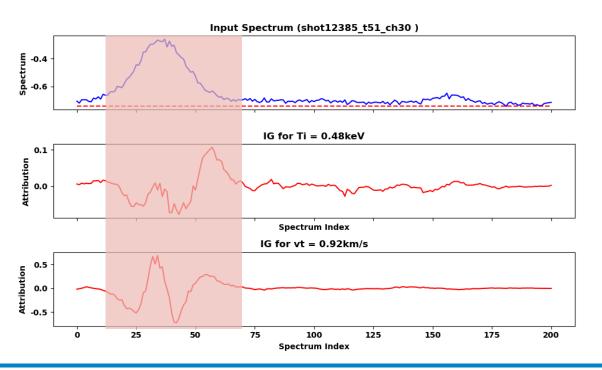


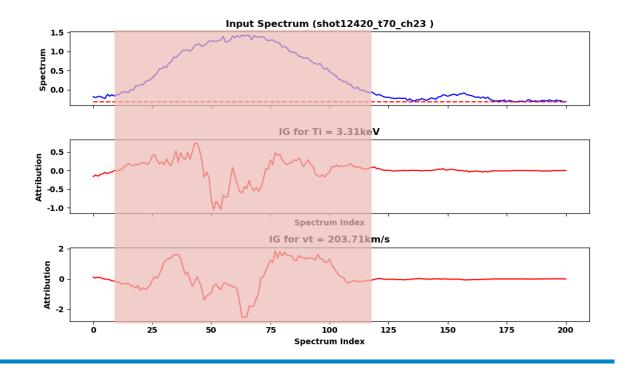
Why interpretability?

To understand and trust the NN model

To guide model optimization

Integrated Gradient:
$$IG_i(x) = (x_i - x_i') \times \int_0^1 \frac{\partial F(x' + \alpha \times (x - x'))}{\partial x_i} d\alpha$$





Interpretability

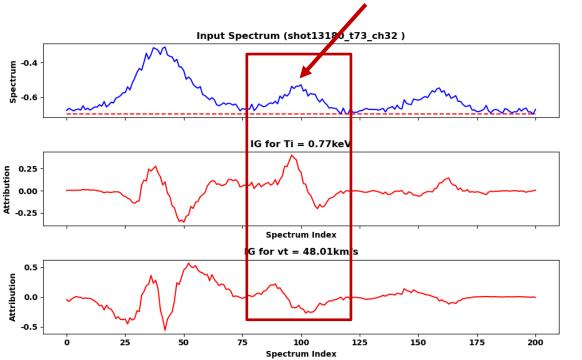
■ Why interpretability?

To understand and trust the NN model

To guide model optimization

Interpretability Diagnoses a Failure:

True Ti: 0.77 keV Affected by 'less-seen' Pred Ti: 2.70 keV interfering spectral peak



- Potential solution: synthetic spectra as data augmentation^[1].
 - [1] Wenjing Tian, et al. Acta Physica Sinica, 74, 078901 (2025)

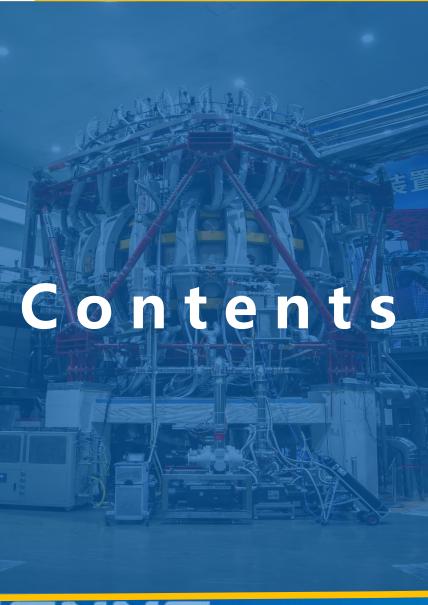
We developed an NN model for CXRS spectral analysis.

High accuracy: reaches R² of 0.93 for Ti and 0.98 for vt

Real-time speed: provide a profile of 32 channels in <1 ms

Interpretable & reliable: Makes decisions based on physically meaningful features.

Parameter	R ²	MAE	MRE	Inference time
Ti	0.933	0.14	9.8%	0.56 ms/ 32 channels
vt	0.980	4.50		



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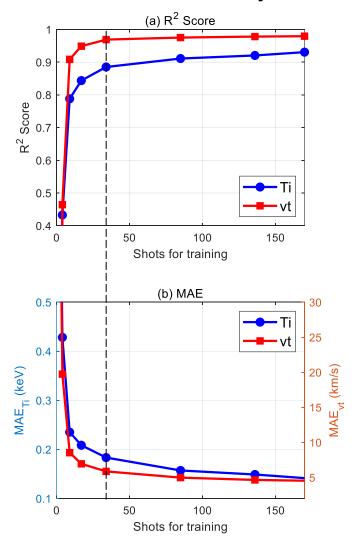
The Data Dilemma

■ Scan the number of shots for training

- ~30 shots
- The more data, the better.

Could spectral data from previous device be of help?

Metrics for HL-3 Only



HL-2A v.s. HL-3 dataset

300

250

50

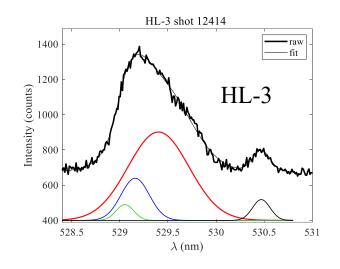
Ti vs vt Joint Distribution

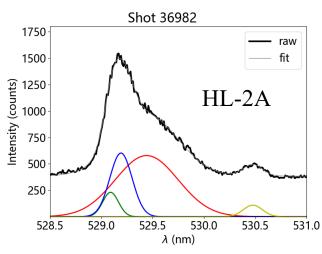
Ti (keV)

HL-3

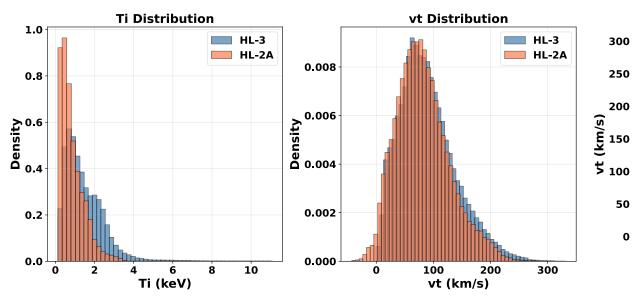
HL-2A

10





Similar components, **Different Spectral structures**



HL-3: 100k spectra from 190 shots. HL-2A: 122k spectra from 89 shots.

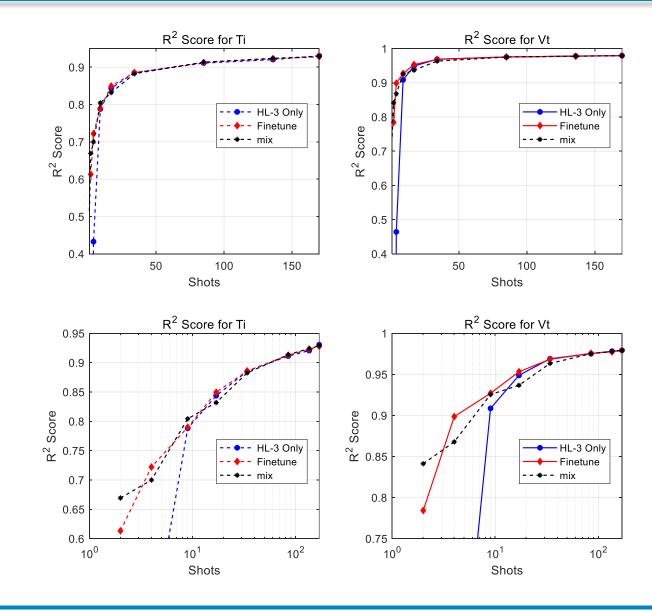


Approaches

Mix: Simply mix HL-2A data into training set. **Finetune**: Pretrain with HL-2A data, finetune with HL-3 data.

Scan the number of HL-3 shots for training.

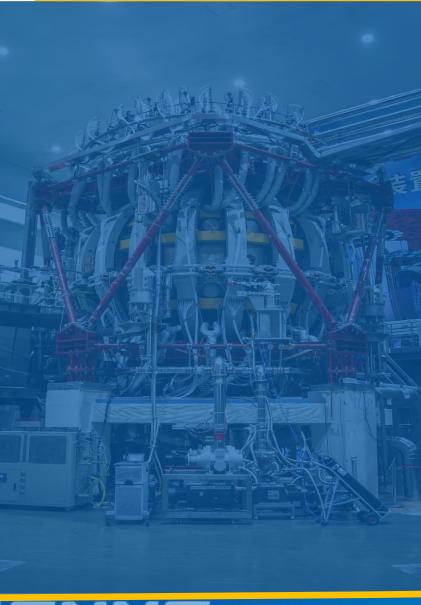
Data from HL-2A helps to get a head start.







- We developed an NN model for CXRS spectral analysis with high accuracy, real-time speed and is interpretable.
- Spectral data from previous device help to get a head start for the NN model in a new device.
- Contribute to the development of AI-assisted plasma diagnostics analysis and real-time control in fusion reactors



Thanks

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