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Fast T_e Profile Reconstructions using Neural Networks

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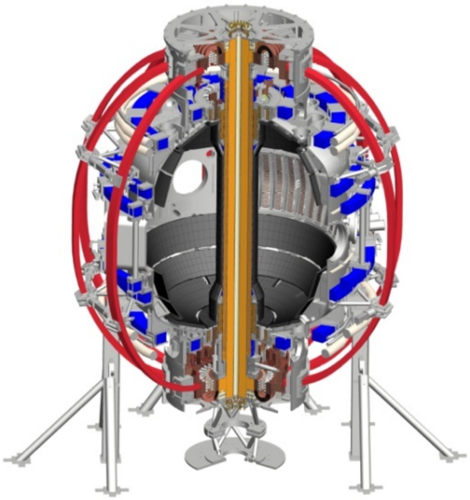

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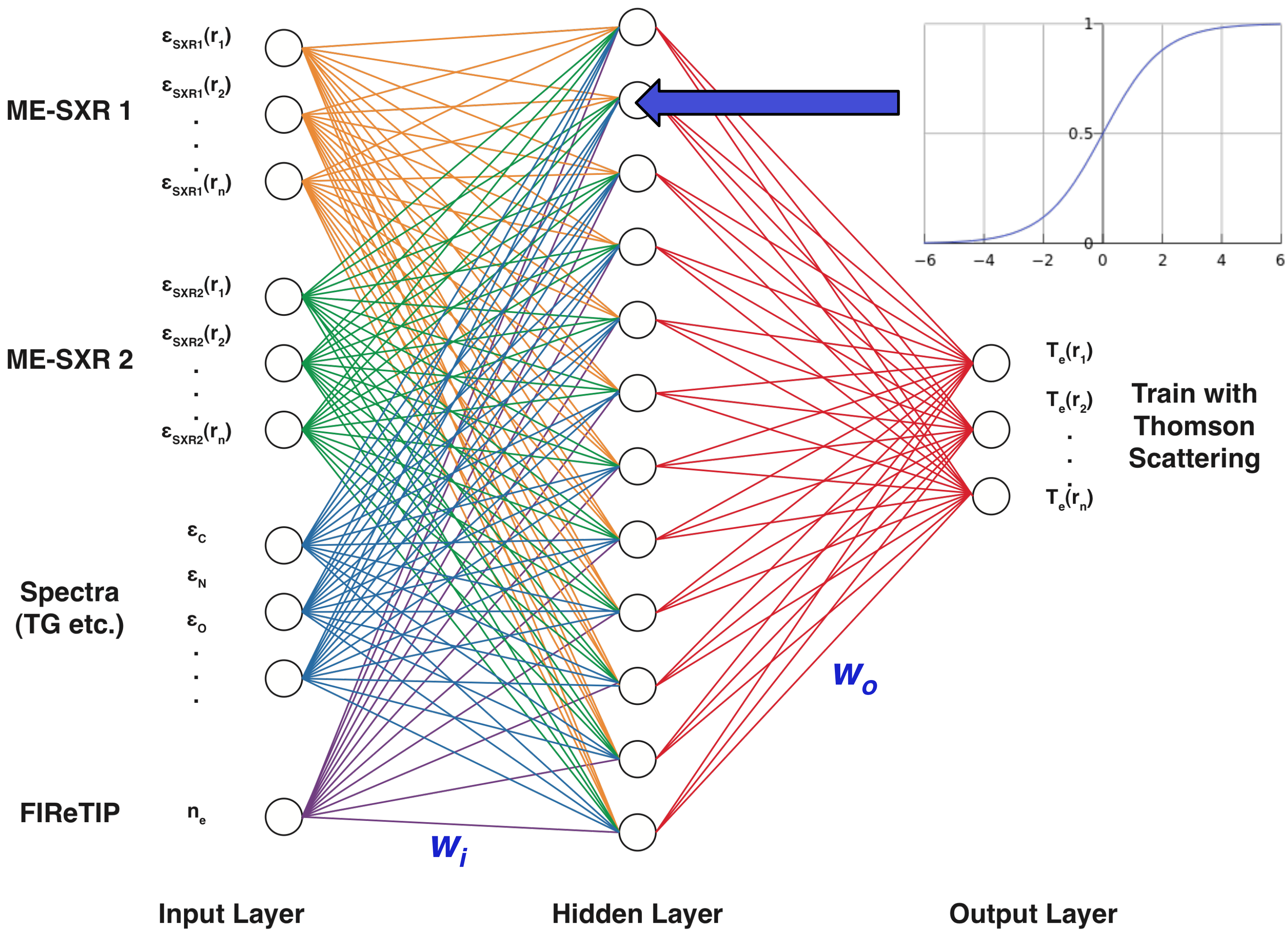
Neural Networks can be Used to Calculate Fast (>10 kHz) T_e Profiles from Multi-Energy SXR Measurements

- Thomson scattering provides 60 Hz T_e measurements
- T_e can also be found from > 10 kHz ME-SXR data, which depend on T_e, n_e, and n_Z, assuming:
  - Proper diagnostic calibrations: brightness, spatial
  - Known spectral response of the filters and diodes
  - Proper atomic emissivity models
  - Proper impurity transport models
- Neural networks, trained with ME-SXR inputs and Thomson outputs, can be used to find T_e without these requirements, and can be used in real time
- These neural networks have been studied with synthetic x-ray data, and successfully tested with real data

A Fully-Connected Three-Layer Neural Network Inputs X-ray and Spectroscopic Data, Outputs Temperature Profiles

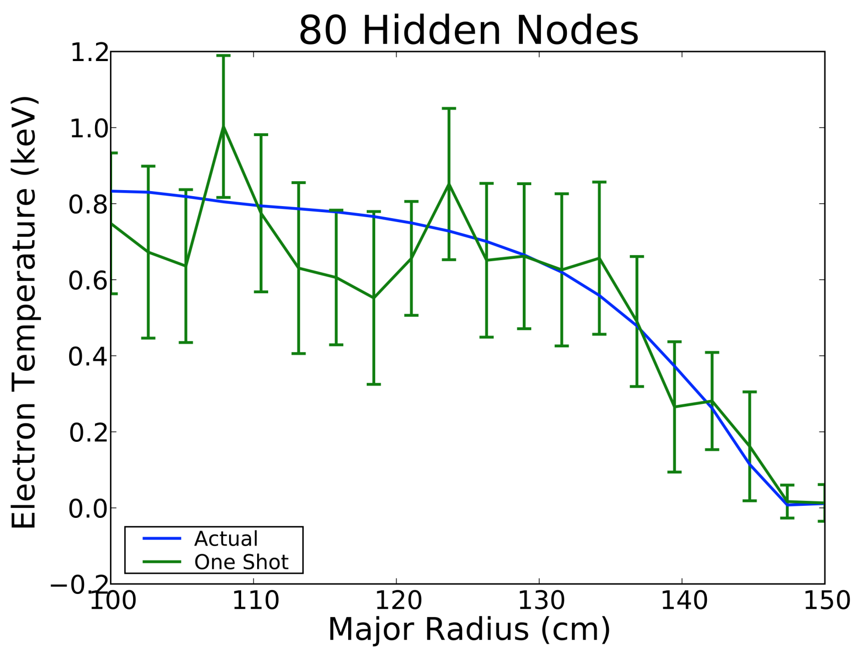


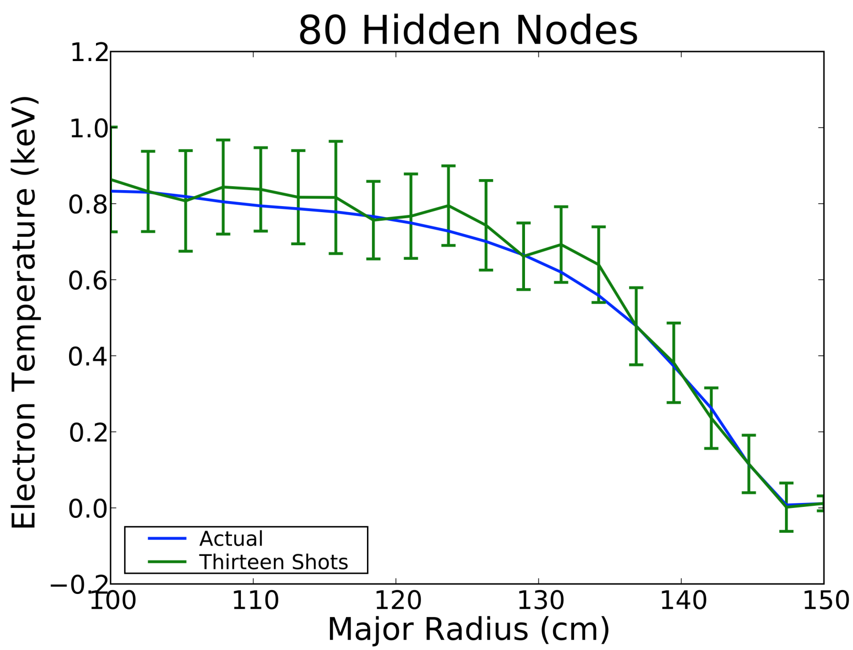
A Simple Feedforward Neural Network Was Tested on Synthetic X-ray, Spectroscopic, and Density Data

- Used PyBrain modular machine learning library for Python
- A three-layer, fully-connected feedforward network
  - Input layer with up to 461 nodes (20 for each ME-SXR array, 400 for the TGIS, 1 for FIReTIP)
  - Hidden layer with an optimized number of sigmoid nodes (usually 40)
  - Output layer had 20 nodes, for temperature profiles with the same radial resolution as the ME-SXR arrays
- Rprop- learning algorithm used for supervised training
  - All input and outputs are scaled to the range of 0 to 1
- Synthetic x-ray data generated from real T_e profiles
  - T_e, n_e profiles from Thomson, n_C profile from CHERS
  - $n_O = 0.2\ n_C$, $n_N = 0.1\ n_C$, $n_{Fe} = 0.001\ n_C$ in coronal equilibrium
  - Gaussian noise added to each signal: 0.5% for ME-SXR, 5% for TGIS, 2% for FIReTIP data

Neural Network Performance Improves as the Training Dataset Grows

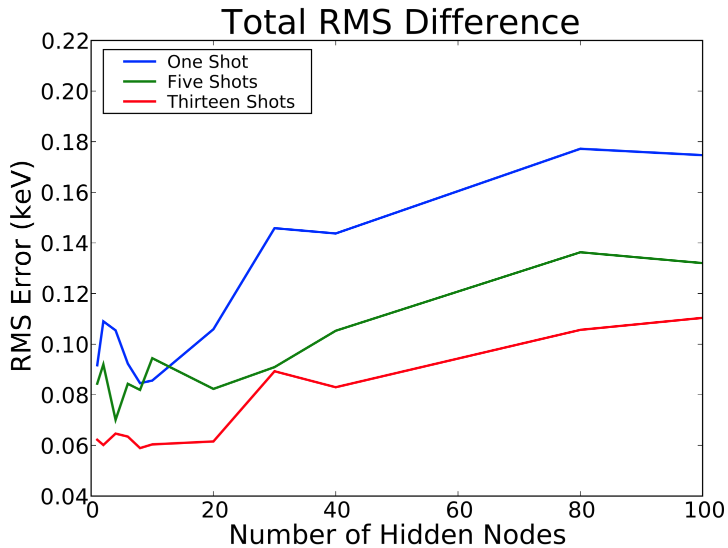
- Each discharge provides ~30-50 Thomson measurements for training (only times with peak T_e > 200 eV were used)
- Test case was tried on a NN trained with one shot, then on a NN trained with 13 shots covering B_T and I_P scans
- Error bars represent total RMS error throughout a discharge

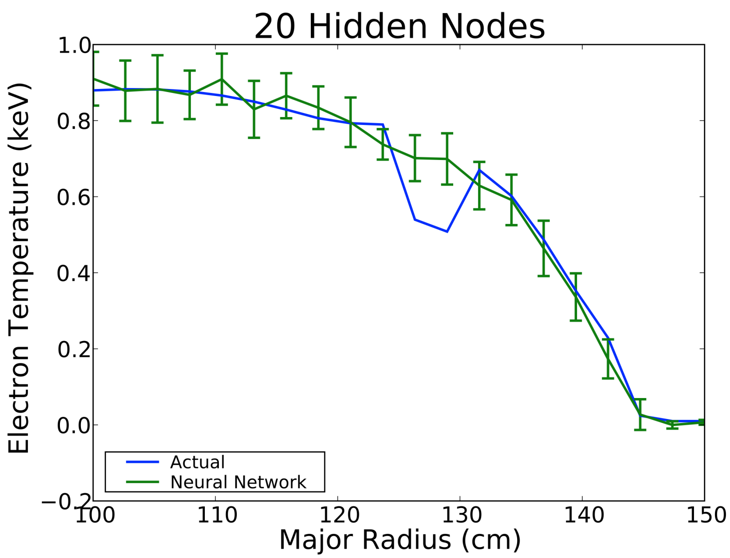


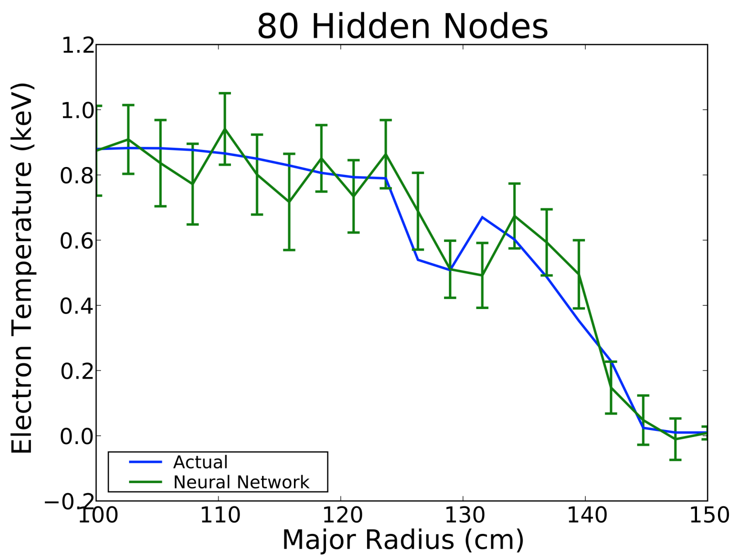


Reducing the Number of Hidden Nodes Smooths Out the Temperature Profile, which can Miss Radial Structures

- Fewer hidden nodes = smaller RMS error
- A "cold pulse" was added to the synthetic data to test sensitivity of the network
  - Too few nodes missed pulse

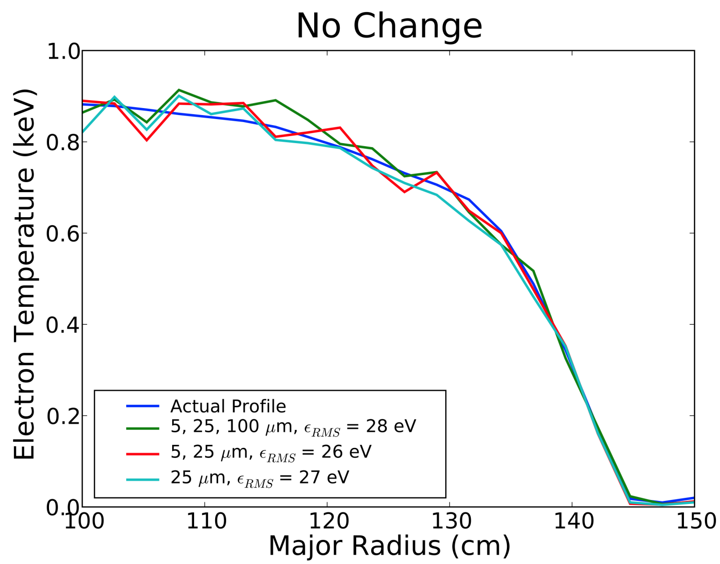


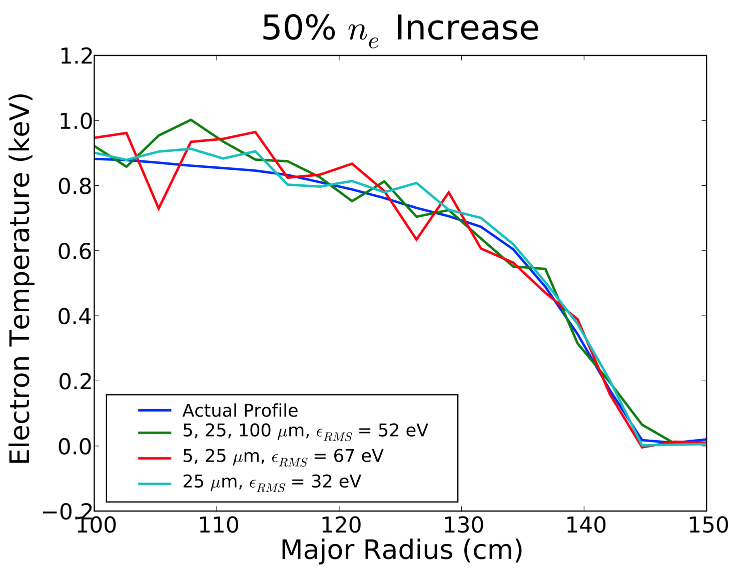


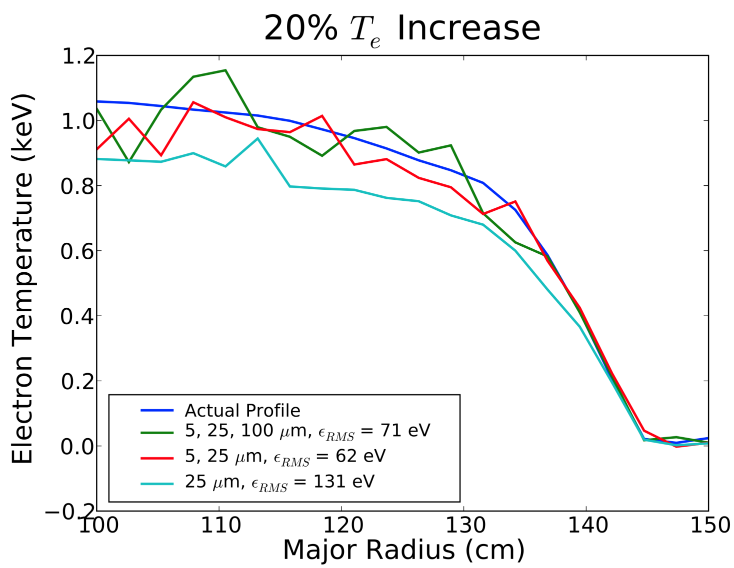


Multiple SXR Arrays are Needed to Distinguish Changing Temperatures from Densities and Impurity Concentrations

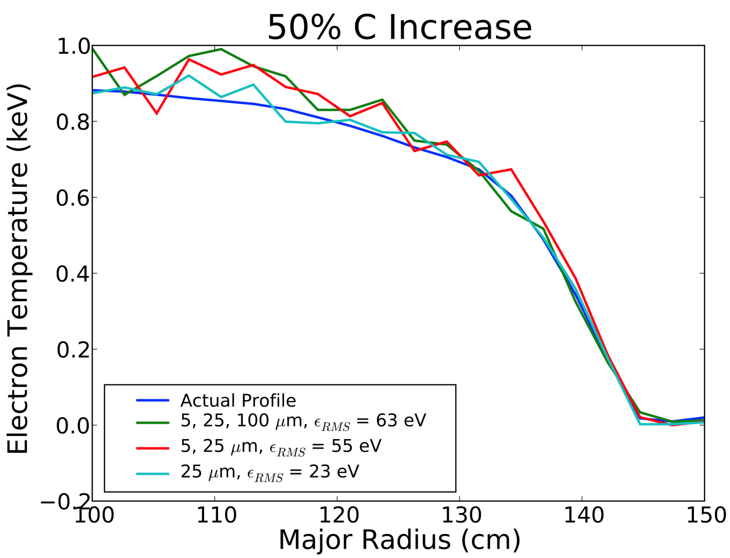
- When trained on one array, network is unresponsive to changes in one parameter
- A third (or more) arrays may be beneficial when several parameters vary independently

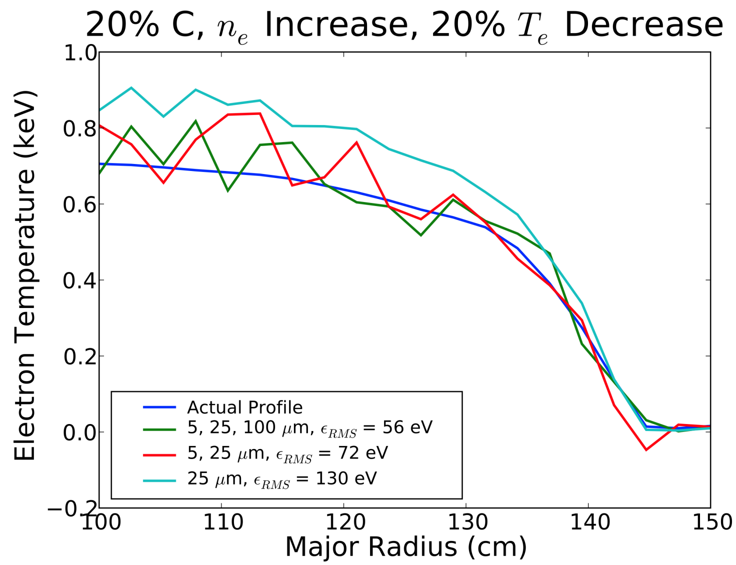


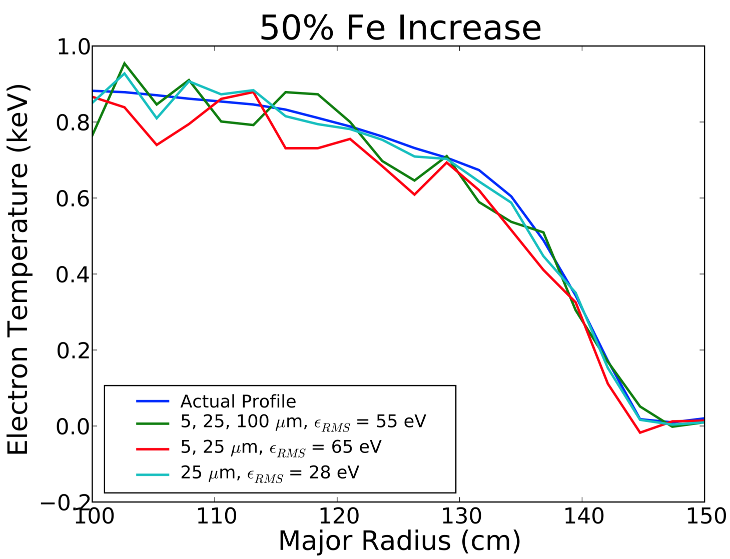


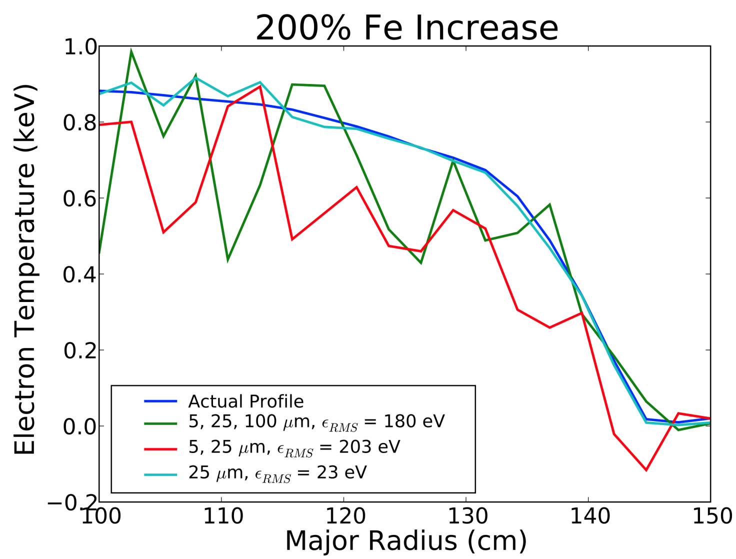


Network Works for Small Changes in Impurity Concentration, but not for Large Influxes that are not Included in Training



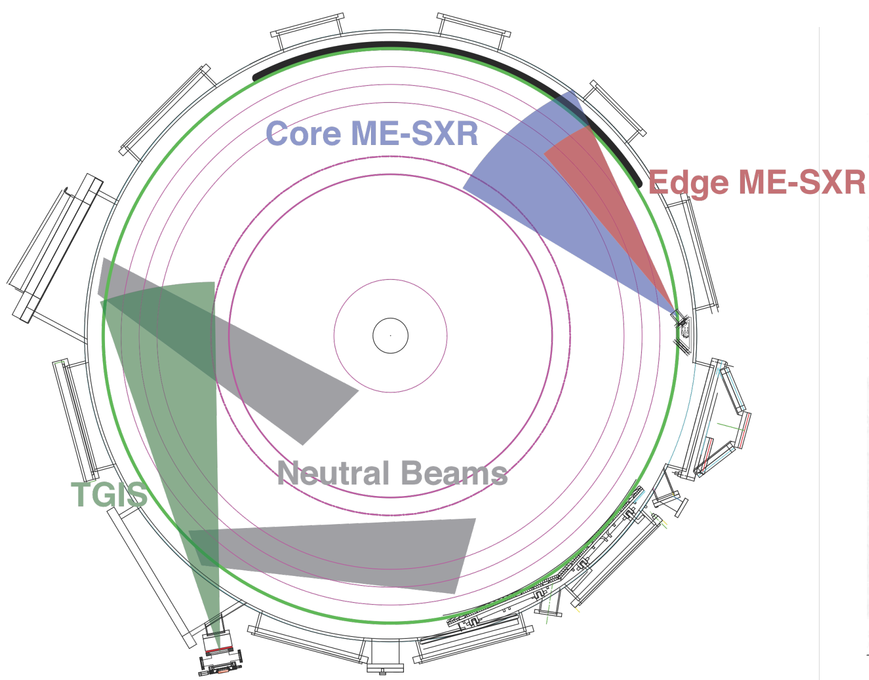


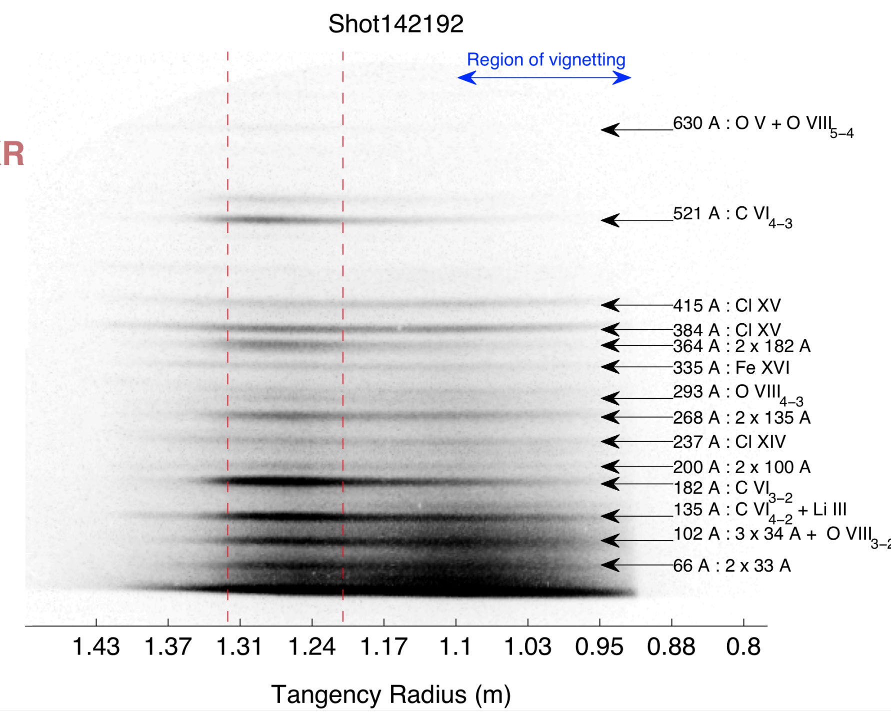




In Addition to ME-SXR, Upgraded TGIS Diagnostic will Provide Constraints on Impurity Concentrations

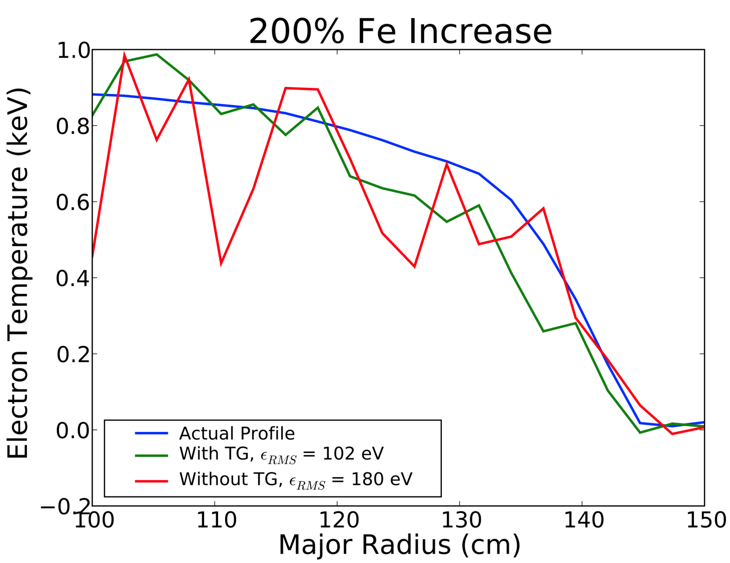
- Radially resolved spectrometer operates in a survey mode covering 30 to 700 Å with spectral resolution $\delta\lambda/\lambda \sim 3\%$.
- Detector time resolution is less than for ME-SXR (400 ms will be upgraded to 10 ms for NSTX-U)

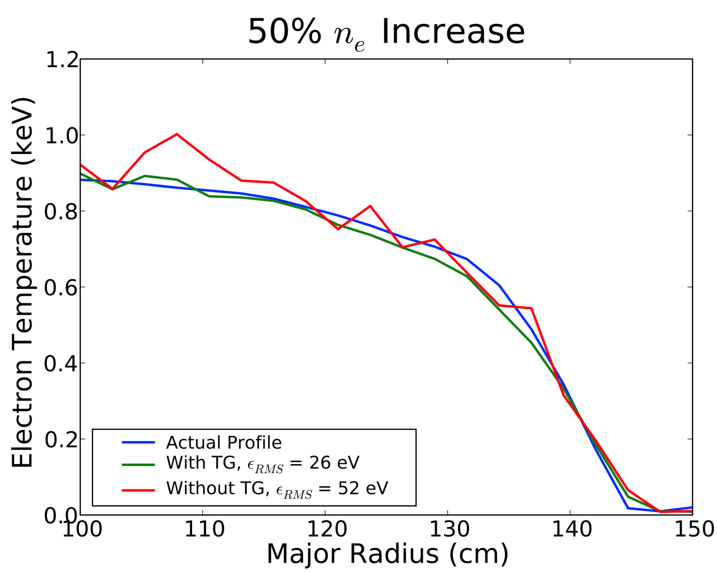




Unexpected Impurity Influx can be Accounted for with TGIS or Other Spectroscopy Data

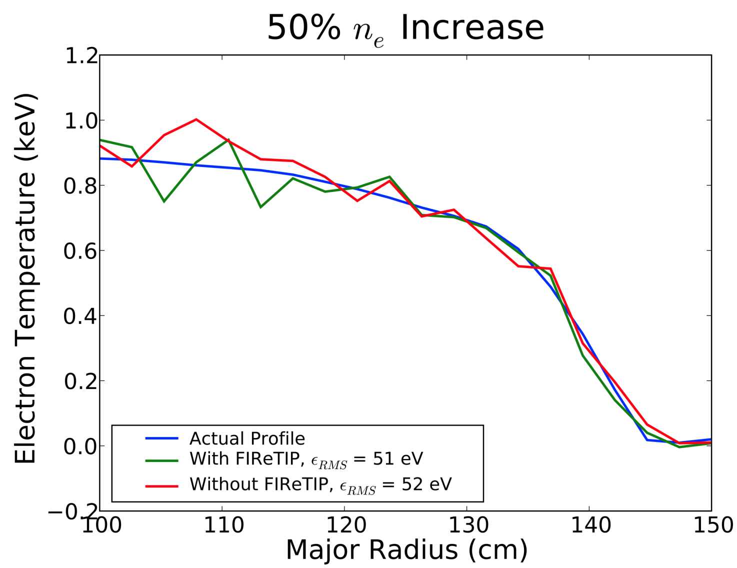
- TGIS greatly improves network performance when impurity or electron densities change
- Other spectrometers (w/o spatial resolution) might contribute additional constraints, or could possibly be used in real-time
- With TGIS, the network might be able to determine n_e, Z_{eff} *profiles* in addition to T_e profile (future work)

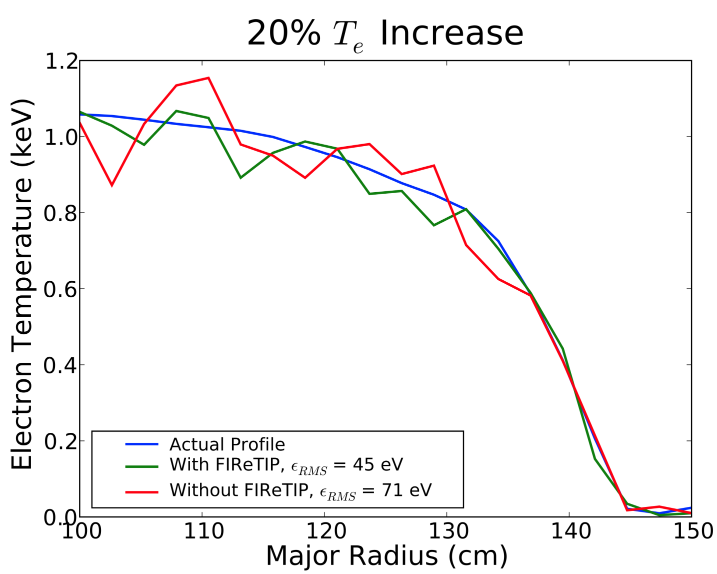


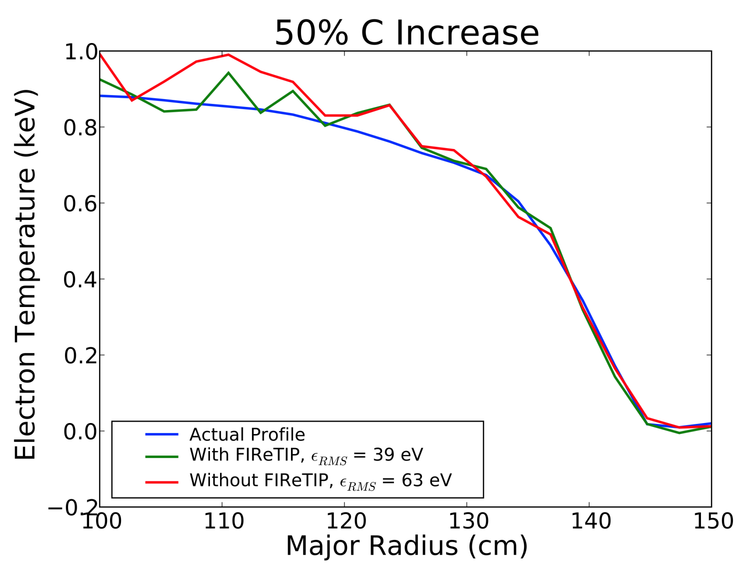


Adding Additional Diagnostics to the Network can Further Enhance Performance

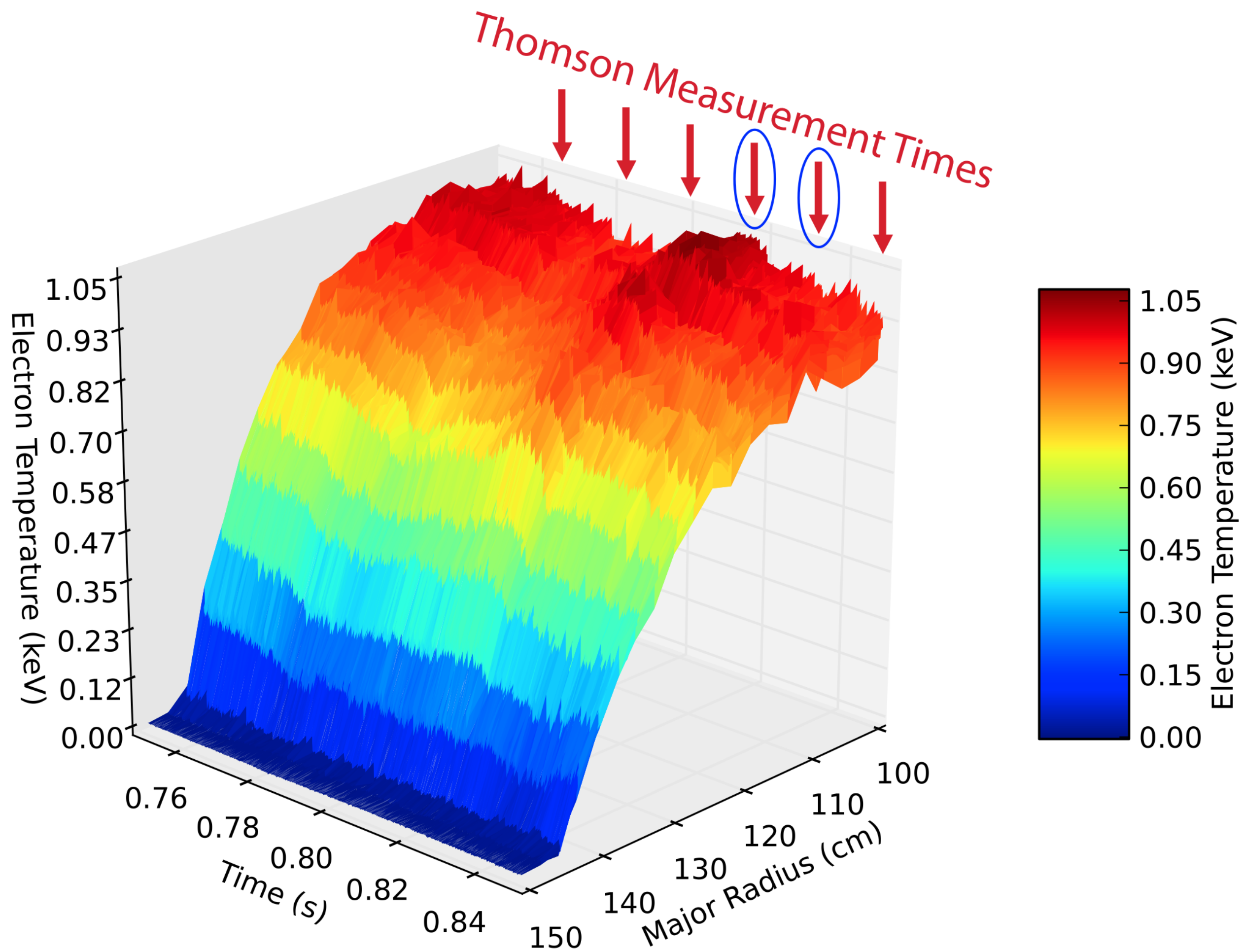
- Adding line-averaged density from the FIReTIP diagnostic improves performance by ~50% in some simulations
- This might be available for a real-time diagnostic



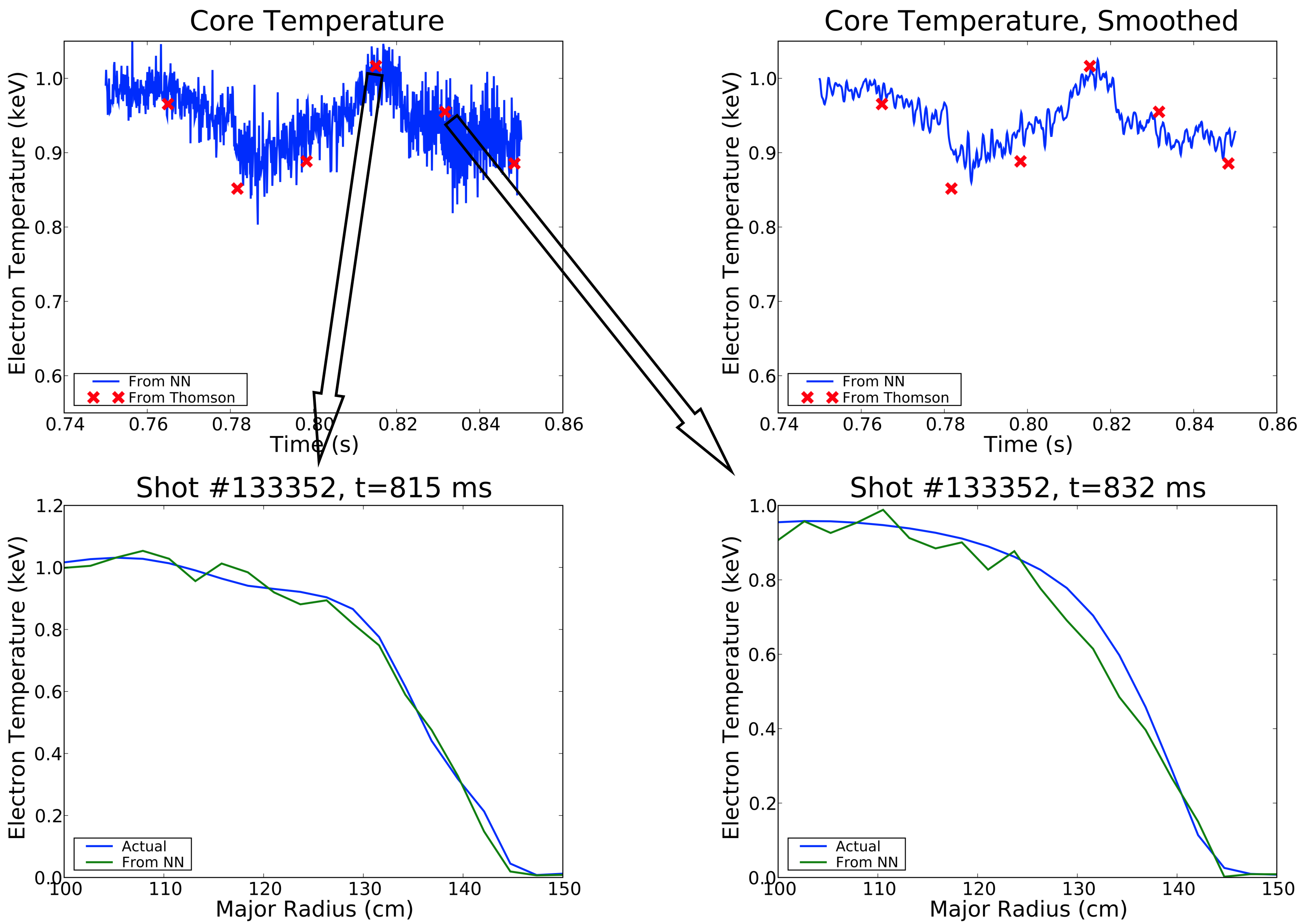




First Test on Experimental Data Used Raw, Uncalibrated Data from Previous-Generation, Three-Array, Optical SXR Array



Trained on 32 Discharges, this Neural Network Produces Fast T_e Profiles in Agreement with Thomson Scattering



Neural Networks have Proven Useful for Fast T_e Measurements and will be Further Investigated and Applied

- It has been demonstrated that neural networks can be used to calculate T_e from ME-SXR measurements
  - Training with larger datasets greatly improves results, and the number hidden nodes must be optimized for the highest accuracy without smoothing over radial features
  - One ME-SXR array is insufficient; a minimum of two are required
  - Adding additional data to the network, such as TGIS and FIReTIP, further improve the accuracy of the results

- Future studies will include:
  - Tests to see if n_e and Z_{eff} profiles can also be found with additional ME-SXR arrays and diagnostics (BES, spectroscopy…)
  - Physics studies using real data from an existing, large optical SXR database