Harvard-Smithsonian Center for Astrophysics

Classifying Supernova Remnant Spectra with Machine Learning

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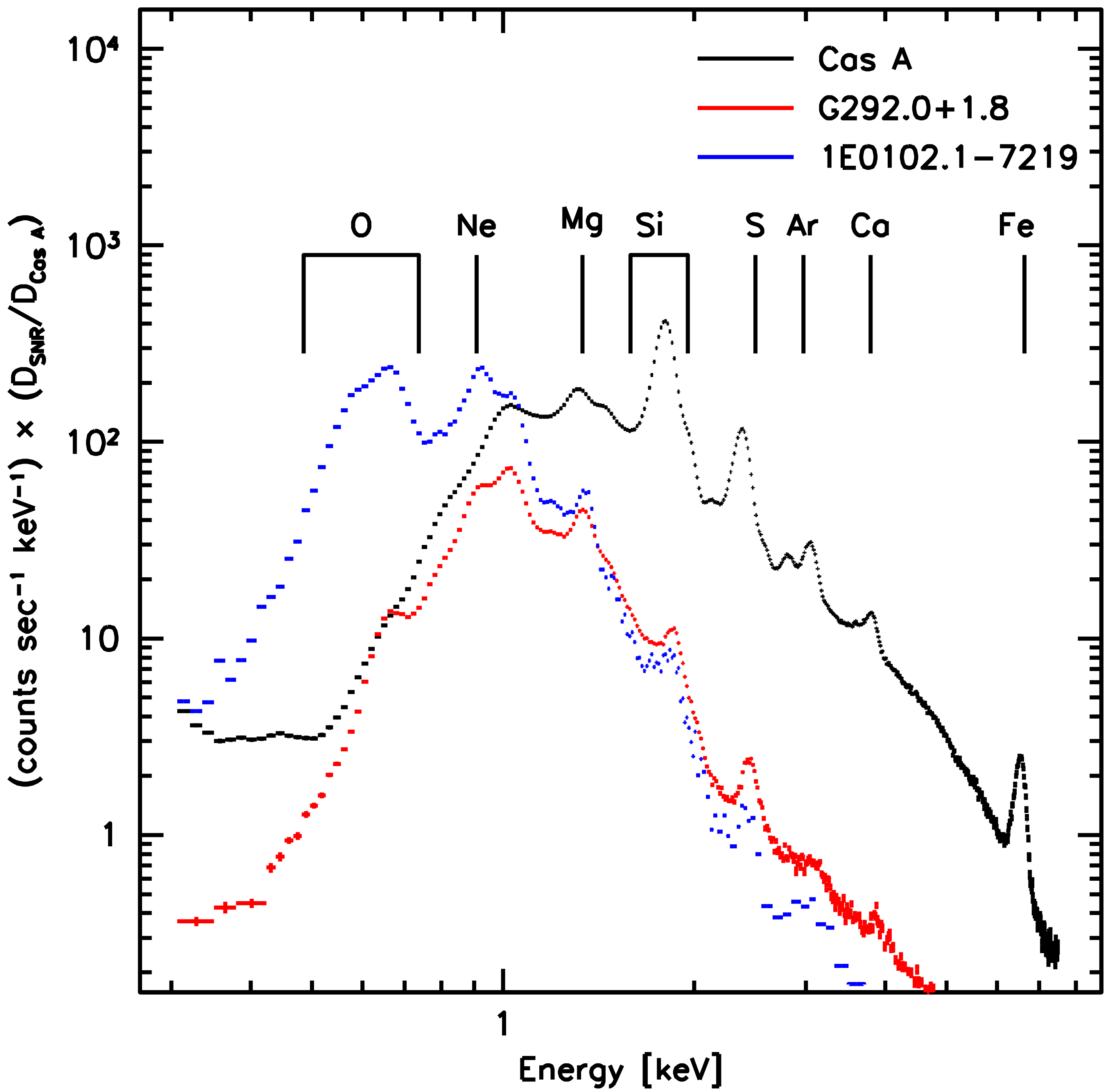
Chandra Theory: TM6-17003X
NASA ATP: 80NSSC18K0566
SI Hydra Cluster Compute Facility

SNR Bulk Properties

- Properties of progenitor's environment and explosion are encoded in bulk properties of X-ray spectra



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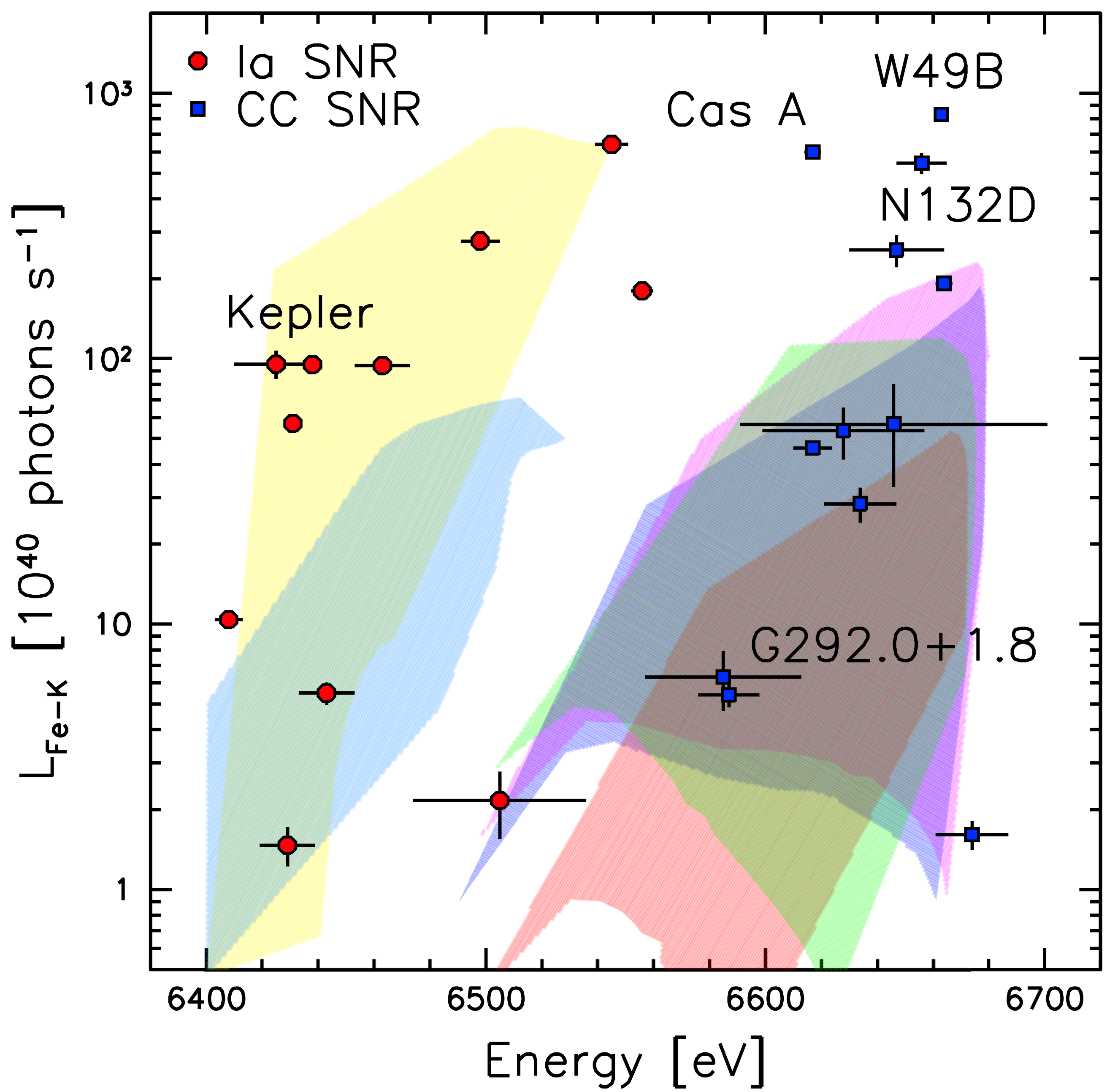
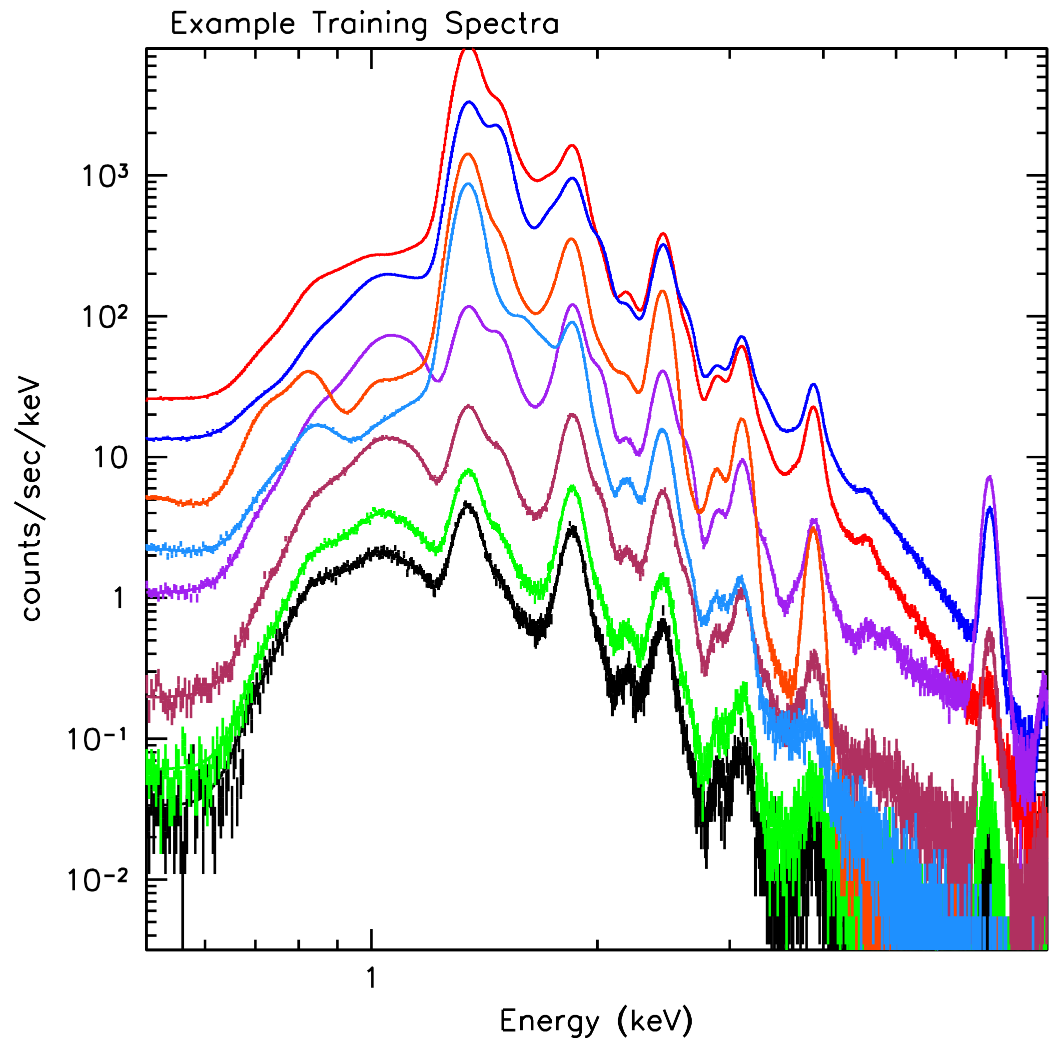


Patnaude et al. (2014)

Machine Learning Training

Synthesized models with varying CSM and ejecta properties:

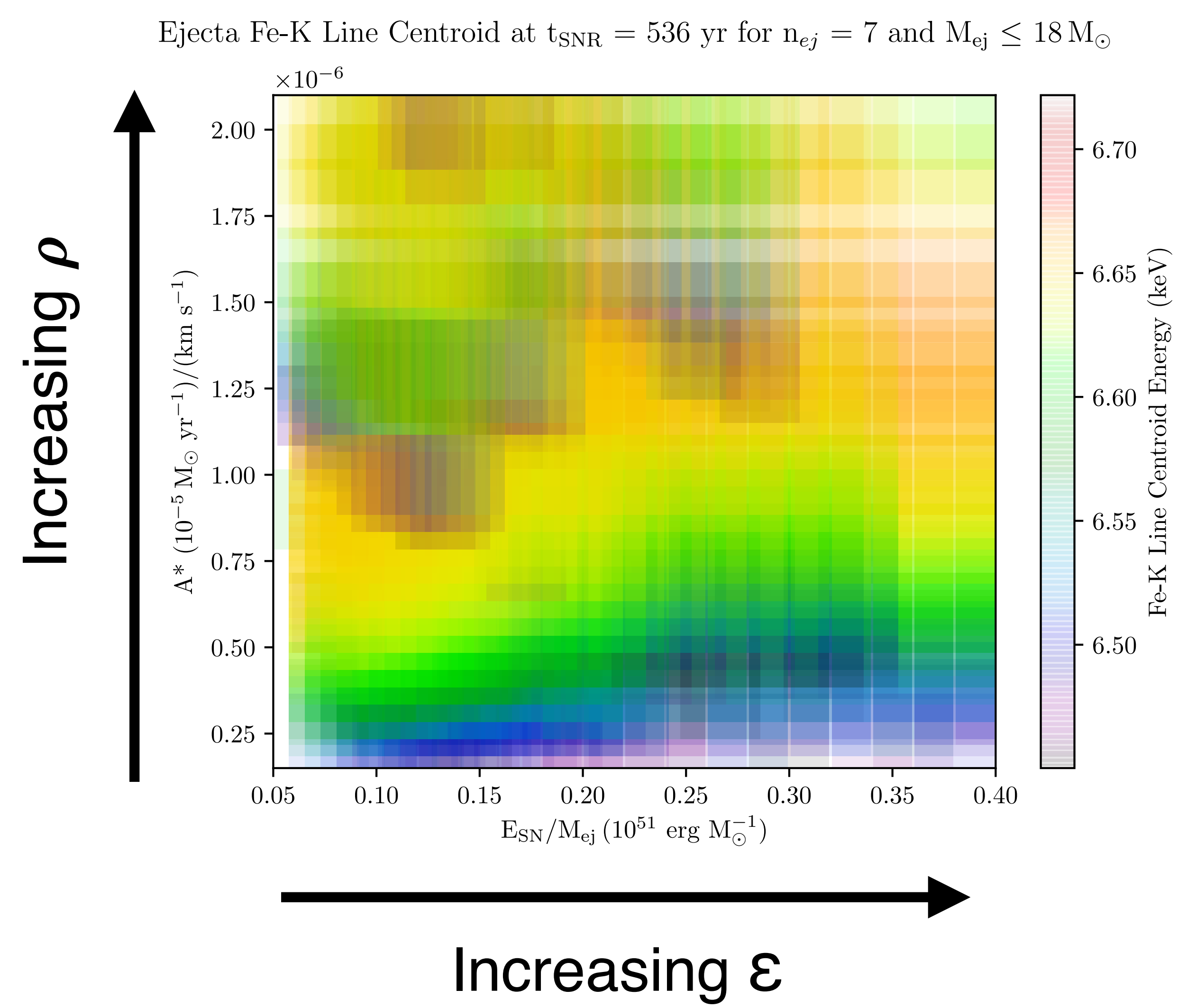
- Mass loss rate and wind speed set progenitor circumstellar environment
- Ejecta mass, explosion energy, and ejecta shape determine dynamics and emission line features
- Simulate evolution to an age of 5000 years
- ~ 45,000 models resulting in ~ 900,000 spectra from shocked CSM and shocked ejecta, with ages from 100 - 5000 years



Machine Learning Training

Use a k-NN classification scheme to study spectral features of models.

- Models are classified based on M_{ej}, E_{SN}, n_{ej}, A*, and t_{SNR}
- Spectral features show clear correlation between explosion parameters (E_{SN}/M_{ej}) and CSM parameters A*
- Spectral features correlate with ejecta density, which relates to progenitor structure



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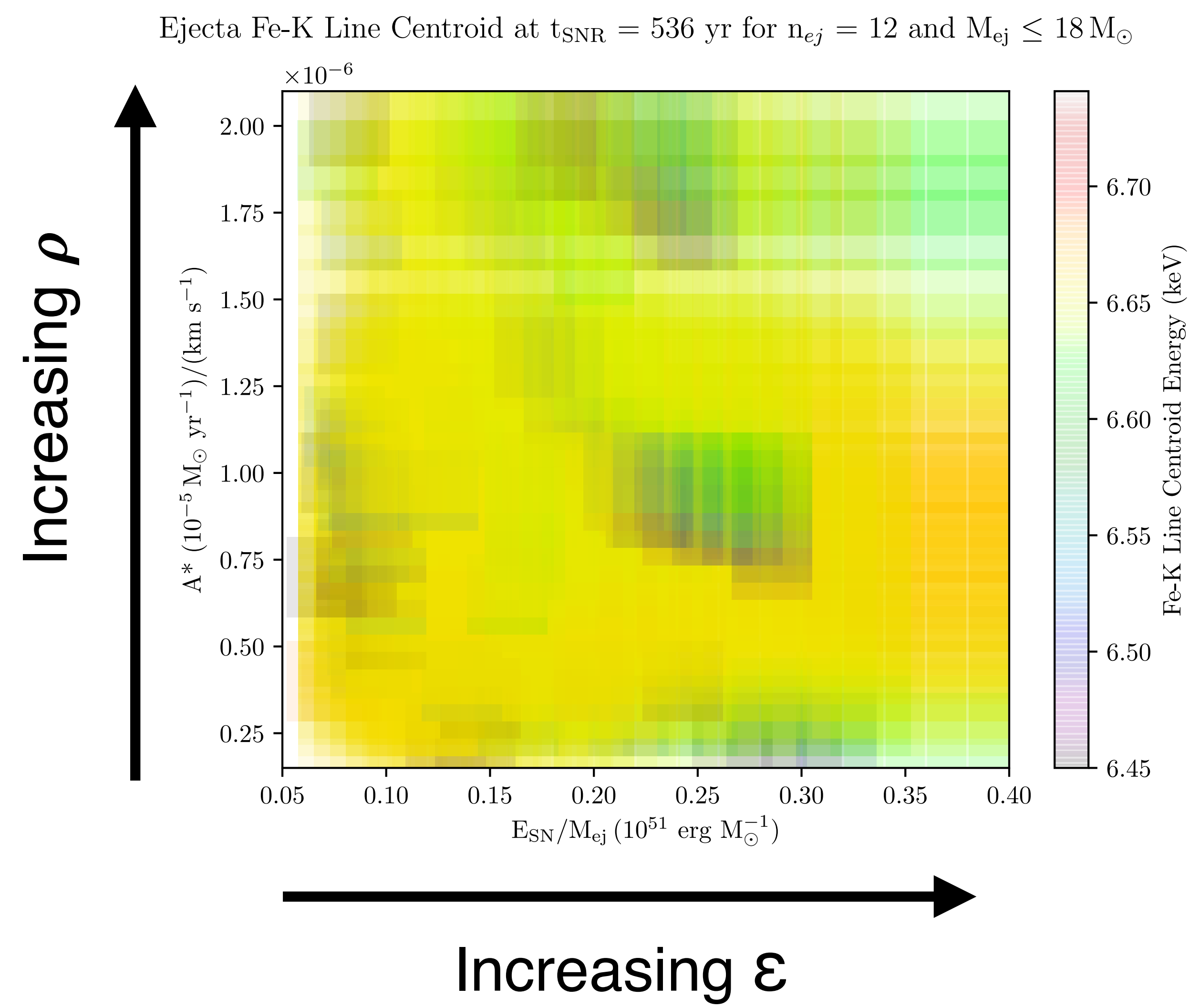
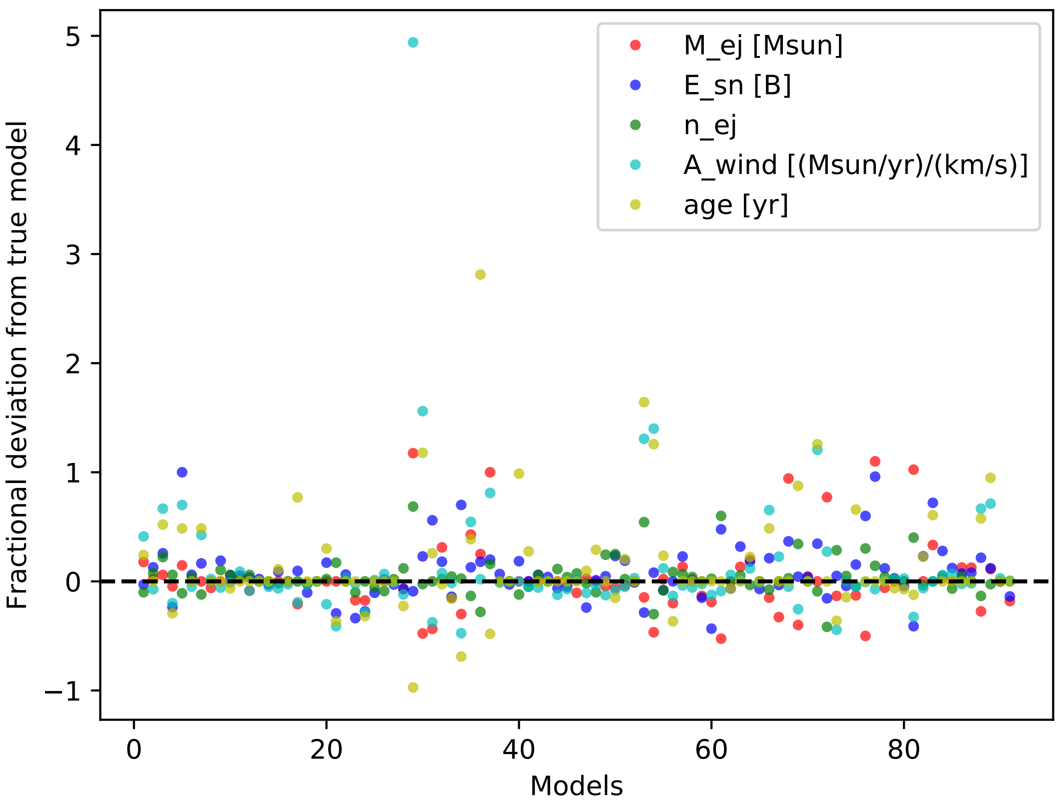


Test Set

Test models are constructed from the training set by randomly sampling the input parameter space and simulating exposures with reduced statistics, by increasing the distance to the source

Test set shows that models are sensitive to distance - distant SNR with poor statistics are mistaken for old SNR evolving into low density environments



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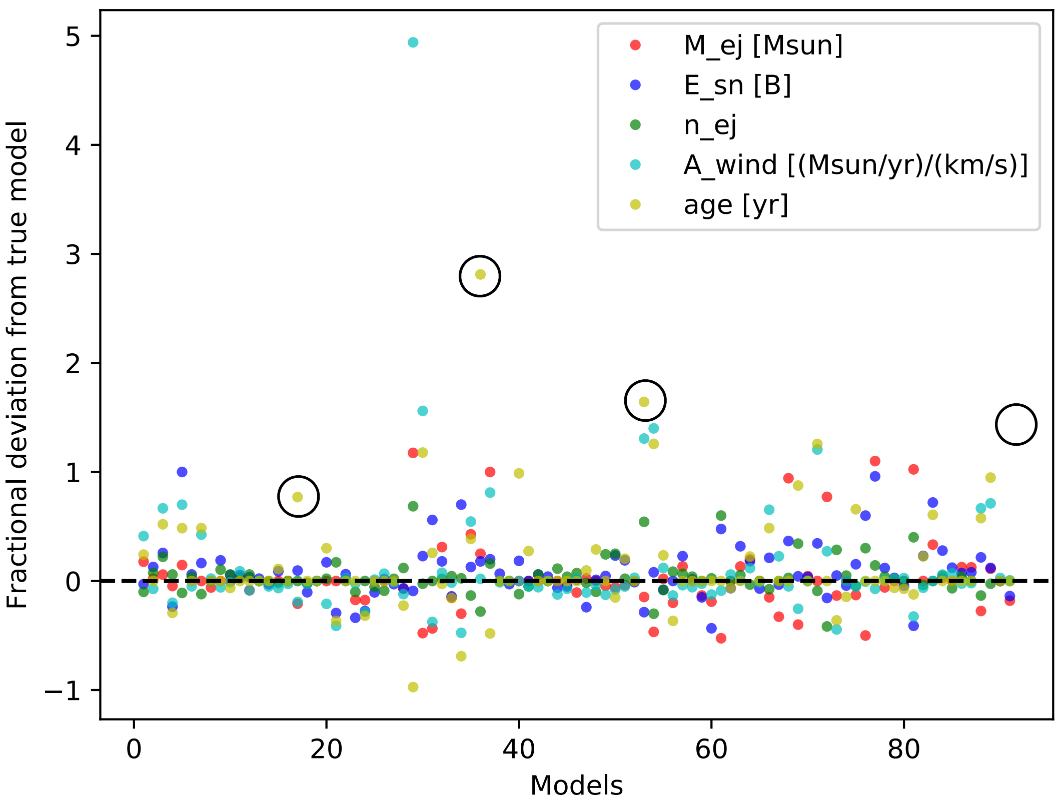

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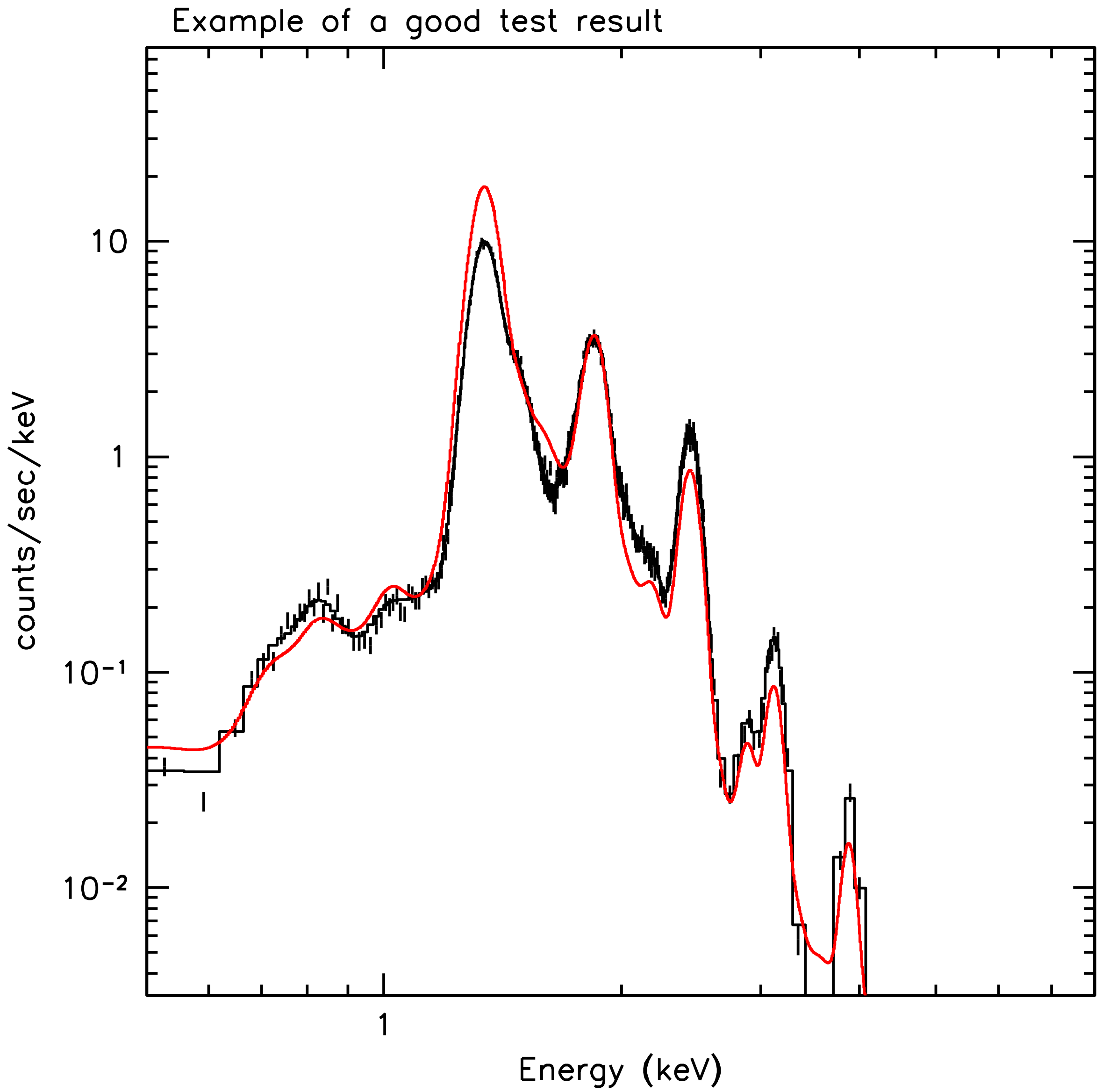

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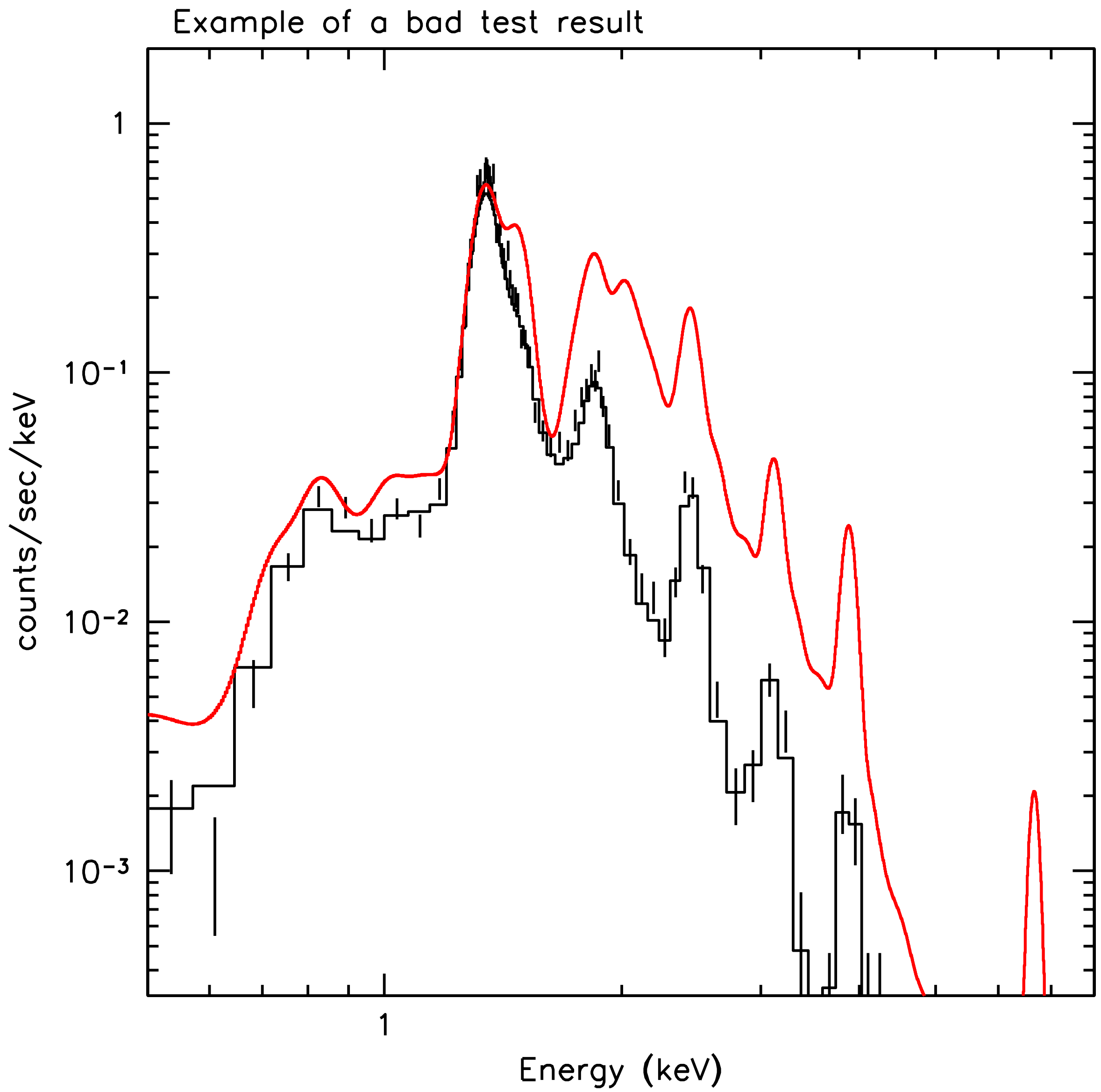
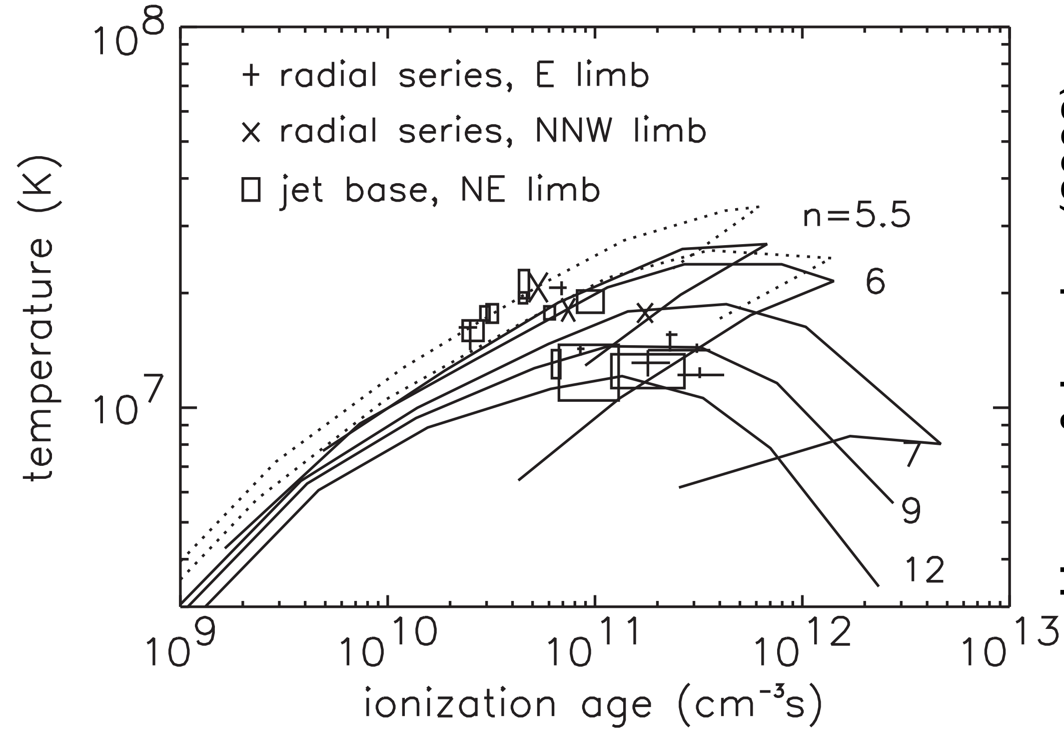
This suggests that when training the model, dynamics (e.g., SNR radius) should be included as an added constraint for model validation



Test Set Refinements

Observations of supernovae and supernova remnants show that asymmetric explosions generally evolve into asymmetric environments

Asymmetric models are created by taking linear combinations of models from the spherically symmetric set (radial flow approximation)



Hwang & Laming (2003)

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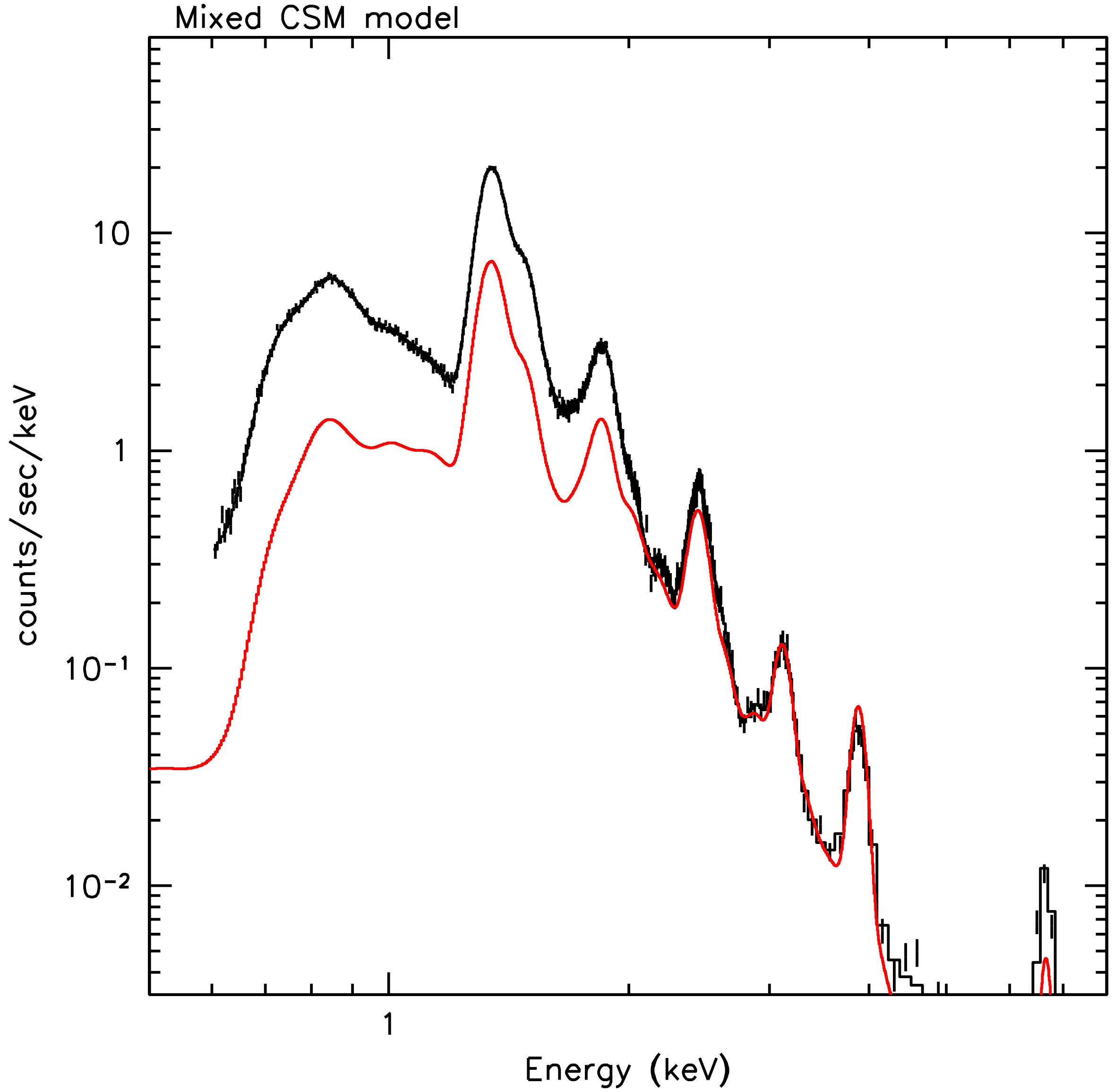

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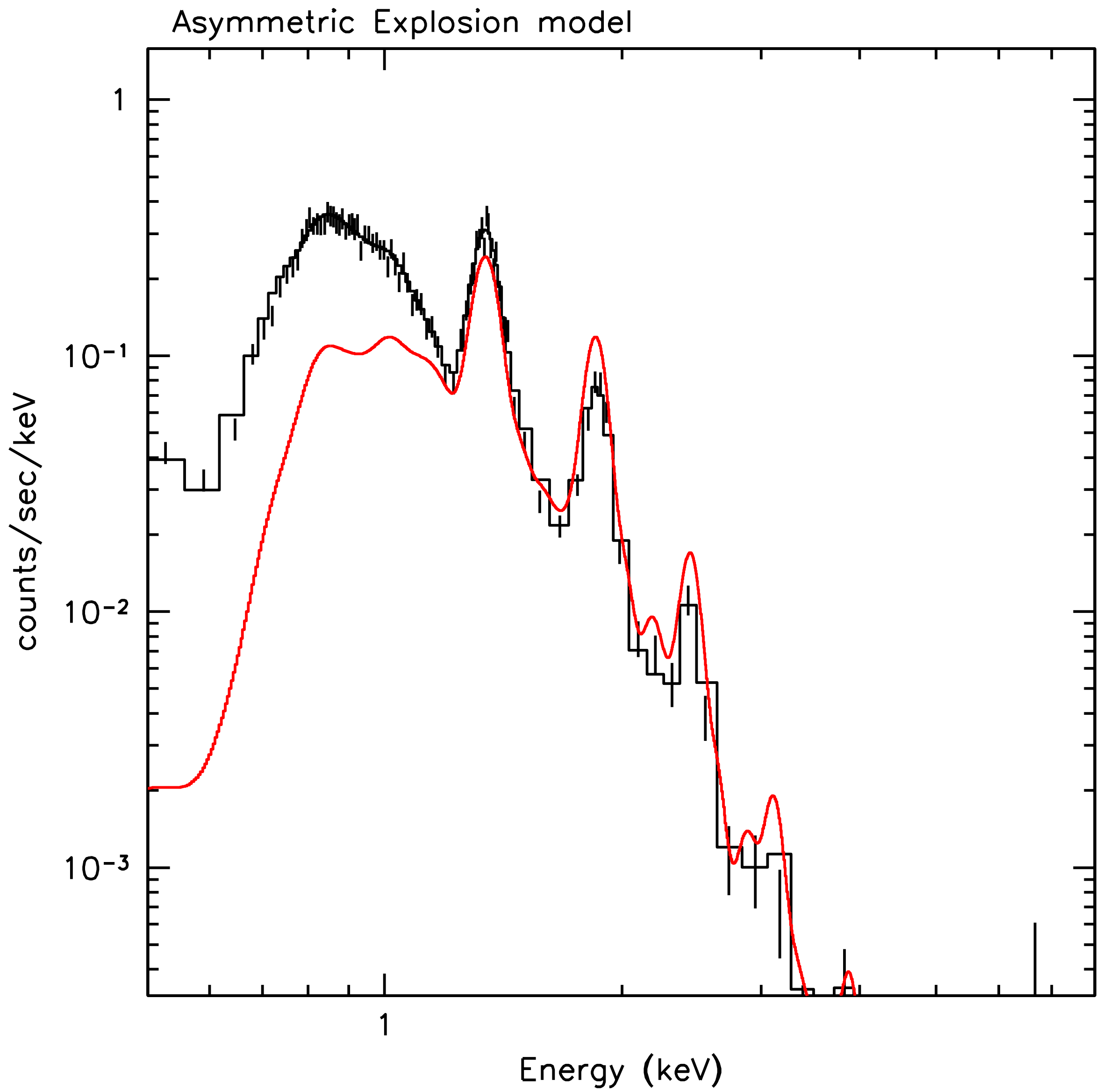

Application to real SNR

SNR G292.0+1.8 (Lee et al. 2010):

- $D_{SNR} \sim 6$ kpc
- $t_{SNR} \sim 3000$ yr
- $A^* \sim 2.5 \times 10^{-6}$

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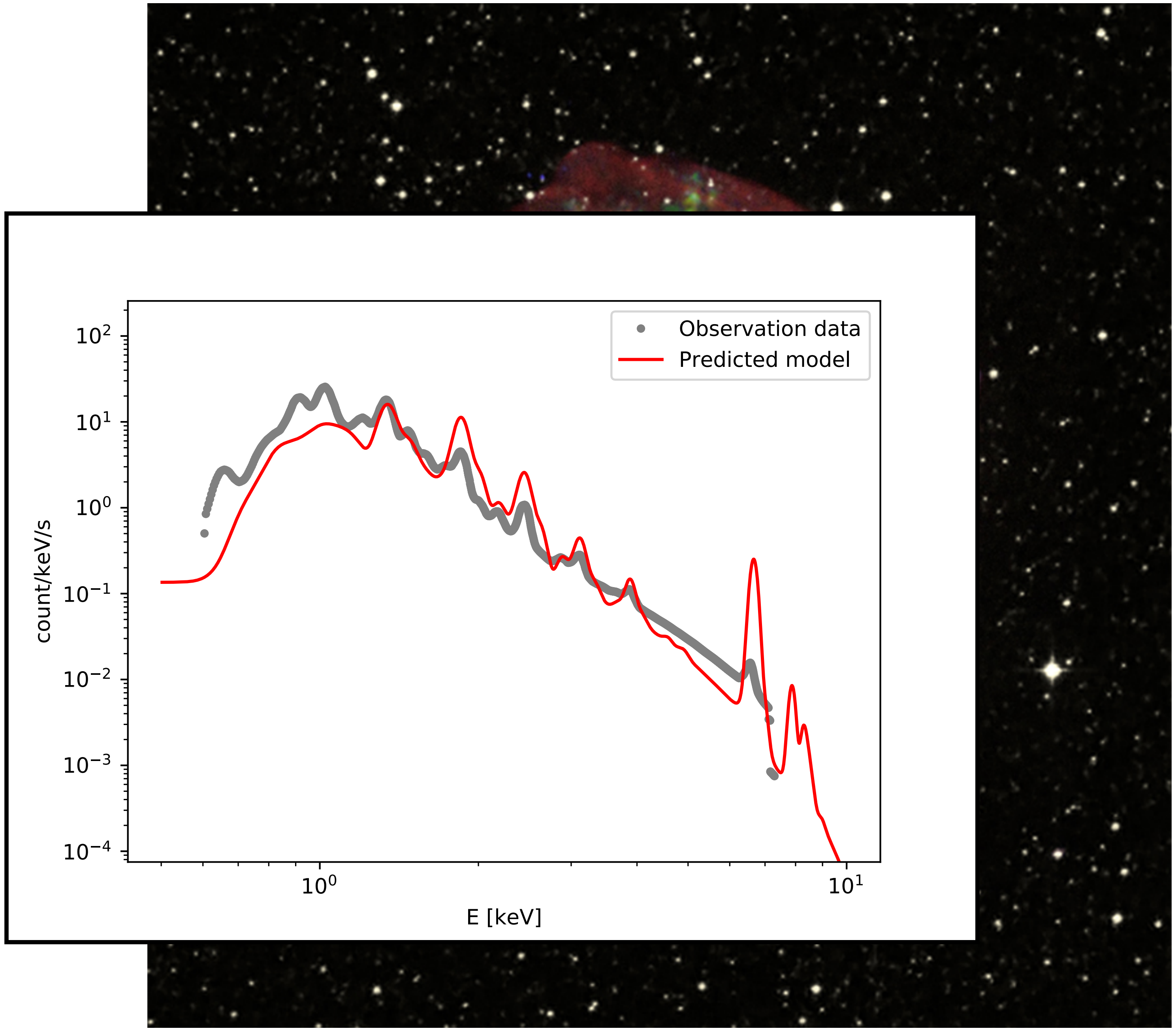
- D_{SNR} ~ 6 kpc
- t_{SNR} ~ 3000 yr
- A* ~ 2.5×10^{-6}

SNR G292.0+1.8 (predicted):
- D_{SNR} ~ 6 kpc
- t_{SNR} ~ 1900 yr
- A* ~ 1.4×10^{-6}
- M_{ej} ~ 18 M_{sun}
- E_{SN} ~ 1.1×10^{51} erg
- R_{SNR} ~ 6 pc



Conclusions

- We trained on synthetic spectra generated from models for 1D CC SNe where we varied properties of the circumstellar environment and explosion
- We tested the trained model by using a noisy sample of the training set, derived by altering the distance and exposure time on certain models
- We simulated spectra from asymmetric CS environments and asymmetric explosions by taking linear combinations of the spherically symmetric models
  - The ML generally overpredicted the age of the SN
- We ran the model against spectra from the Galactic SNR G292.0+1.8
  - The model was unable to find a good match to the input spectrum
  - The environments and explosions of CC SNRs are inherently asymmetric - a refinement to the model would be to train on randomly created asymmetric models
- Refinements include training on SNR dynamics (e.g., radius) and mixed models