Simulation-based inference is "better" at analyzing piled-up X-ray observations.

An ML engineer? Learn about calibrating normalizing flows.

An X-ray astronomer? A novel way to analyze piled-up spectra.

Modeling X-ray photon pile-up with a normalizing flow

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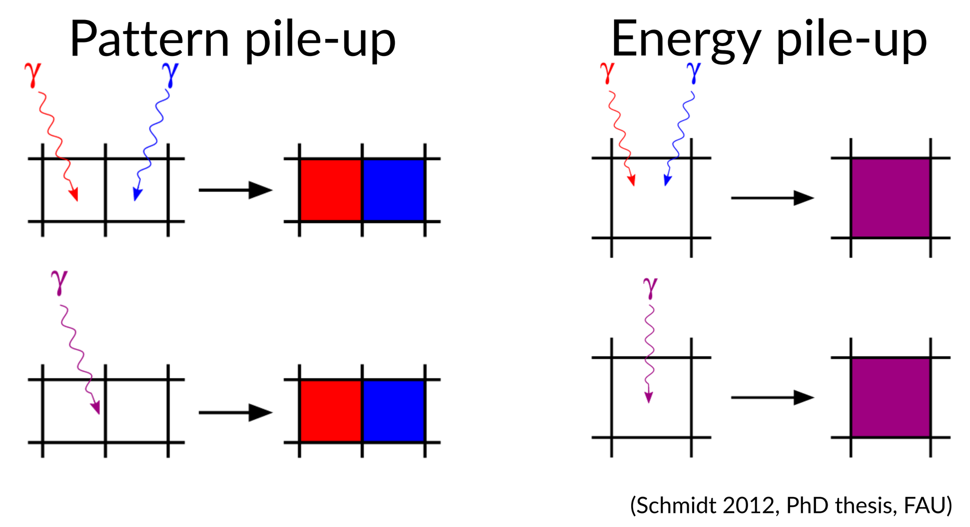
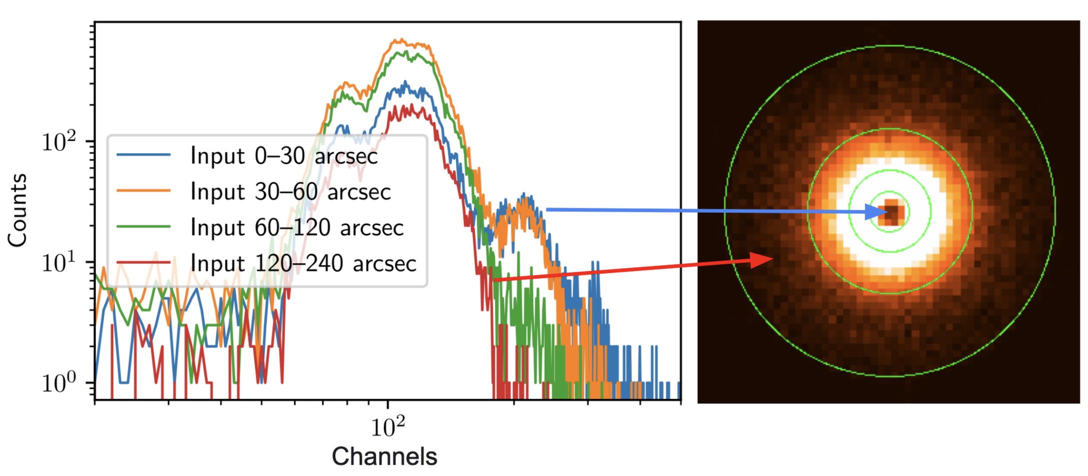
What is photon pile-up?



Events in an X-ray charge-coupled device.

Most X-ray detectors are built on the assumption that each event corresponds to **one photon**. Multiple impacting photons **cannot be distinguished**, which leads to **distortion** of the data and, at the extreme level, to **data loss**.

Our Input: We simulate astrophysical spectra of blackbody emitters, alike to observations of tidal disruption events or novae with the eROSITA telescope. Because pile-up strongly depends on how the photons are spread over the focal plane's pixels, we supply four **spatially-resolved spectra**.

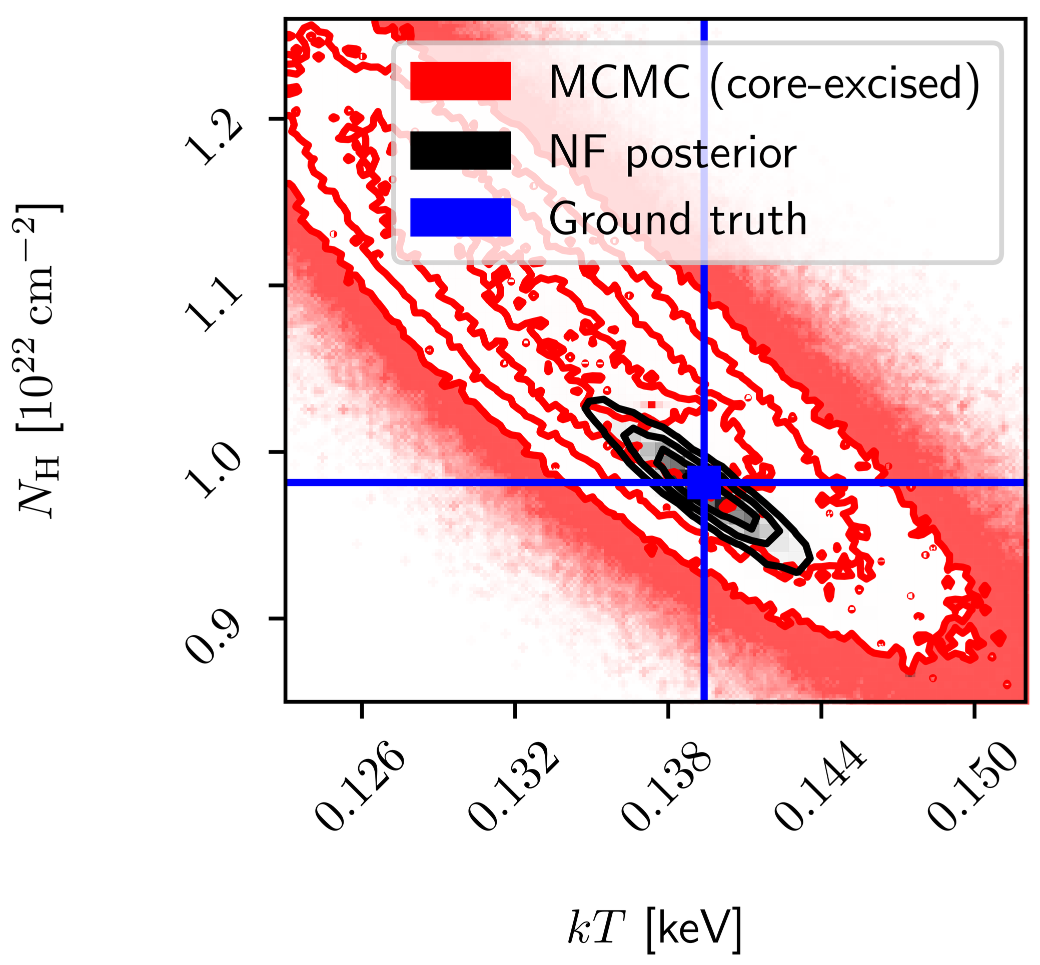


Simulated spectrum and image of a point source.

Our Method: We pass the input spectra through a CNN to compress them into a **lower-dimensional "context" vector**. This vector is passed into the **normalizing flow** which outputs the posterior probability distribution of three physical parameters: flux, temperature, and interstellar gas absorption.

Better than what?

Traditional "core-excising" methods only analyze data from the **outer regions of the detector**. Data in the central region is too distorted from pile-up and is usually **thrown away**.



Because our approach uses **all the available data**, we leverage more signal. The result is a significantly **better constrained posterior** compared to the traditional method.

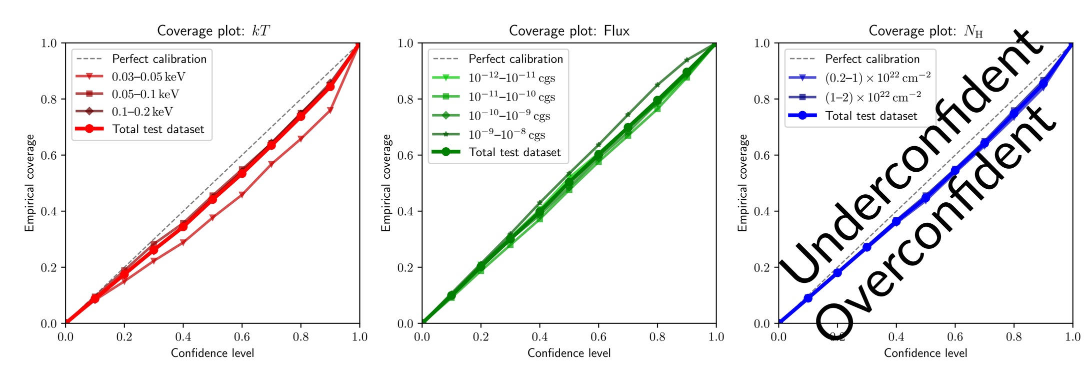
Why SBI?

Simulating realistic piled-up data from astrophysical parameters has become possible with the `SIXTE` simulator[a] (Dauser et al., A&A 630, A66, 2019). The stochastic nature, however, leads to **intractable likelihoods**. SBI is an efficient way to learn the pile-up prescription from **noisy, simulated data** without requiring likelihood evaluations. Once the network is trained, the inference is **amortized**. Inferring posterior distributions of the parameters can be achieved **efficiently** on large amounts of data.

[a] www.sternwarte.uni-erlangen.de/sixte

How do we verify the output?

Normalizing flows tend to be **overconfident**. We use **coverage plots** to assess the calibration. We determine into which percentile of the distribution the ground truth falls. A perfectly-calibrated posterior should have, for instance, 20% of ground truth values fall within 20% of the distribution.



Overall, we find **good calibration**, especially for the flux parameter.

Next, we measure the mean relative error to assess the **accuracy** of the prediction. It is **well below the 10% systematics** to which the forward model is calibrated to.

What's next?

How **much** better is the SBI approach compared to traditional methods? To answer this question, we will simulate all **true posterior distributions** of the test dataset.

Astrophysical sources almost never are pure blackbody emitters. We will increase the training dataset to a **library of spectral models** with different observation strategies, with the ultimate goal of **applying it to X-ray data archives**.