Quantum Matter Matters !

Laboratory for Quantum Matter Research - Prof. Johan Chang

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Magnetic Excitations in Strongly Correlated Materials - RIXS

Using resonant inelastic x-ray scattering (RIXS), we investigate the magnetic excitations in infinite-layer $PrNiO_2$ thin films for different substrates, so different strain conditions. The magnon bandwidth of $PrNiO_2$ shows only marginal response to strain-tuning, in sharp contrast to the striking enhancement of the superconducting transition temperature T_c in the doped superconducting samples. These results suggest the enhancement of T_c is not mediated by spin excitations and thus provide important empirics for the understanding of superconductivity in infinite-layer nickelates.

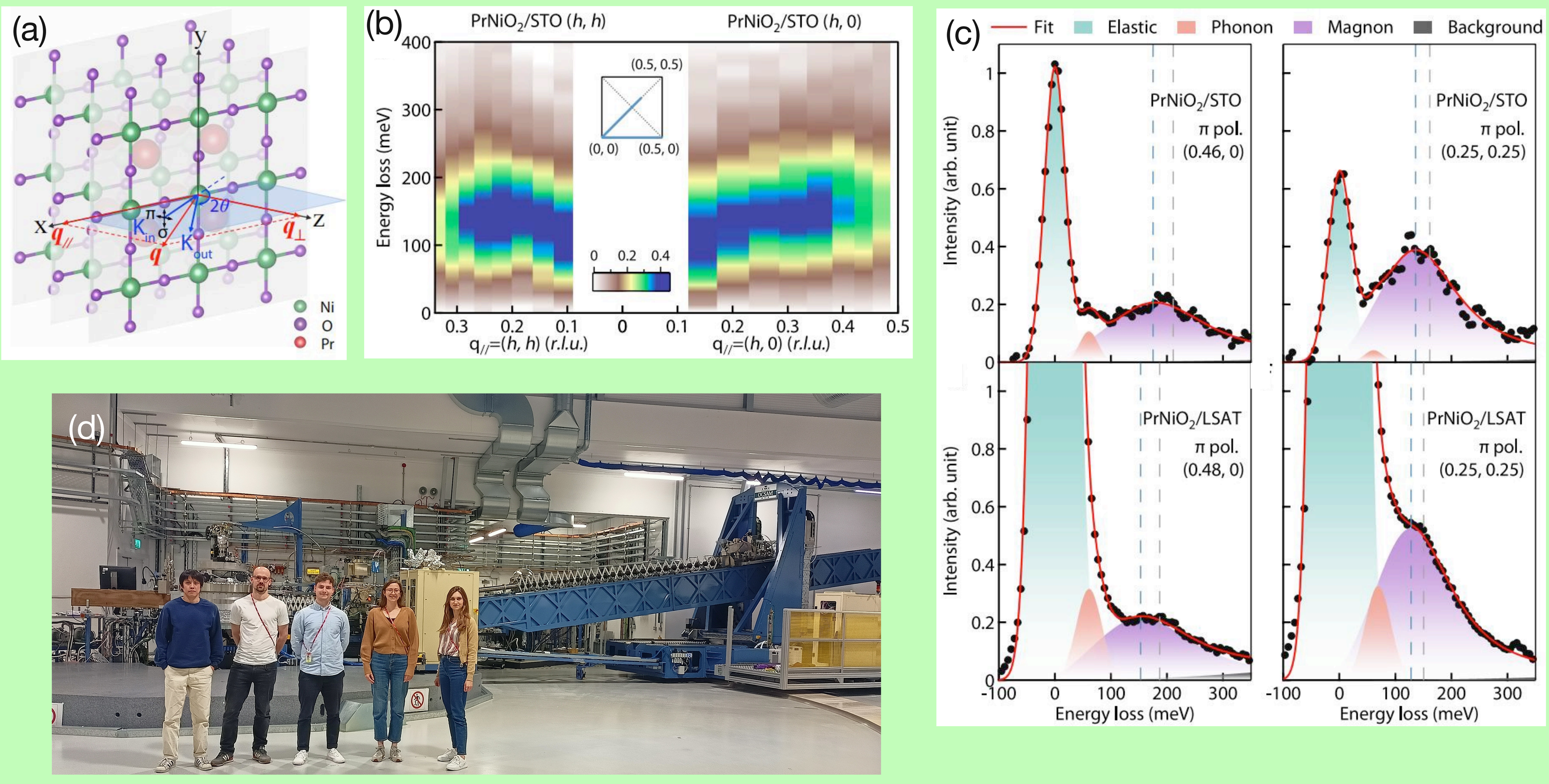
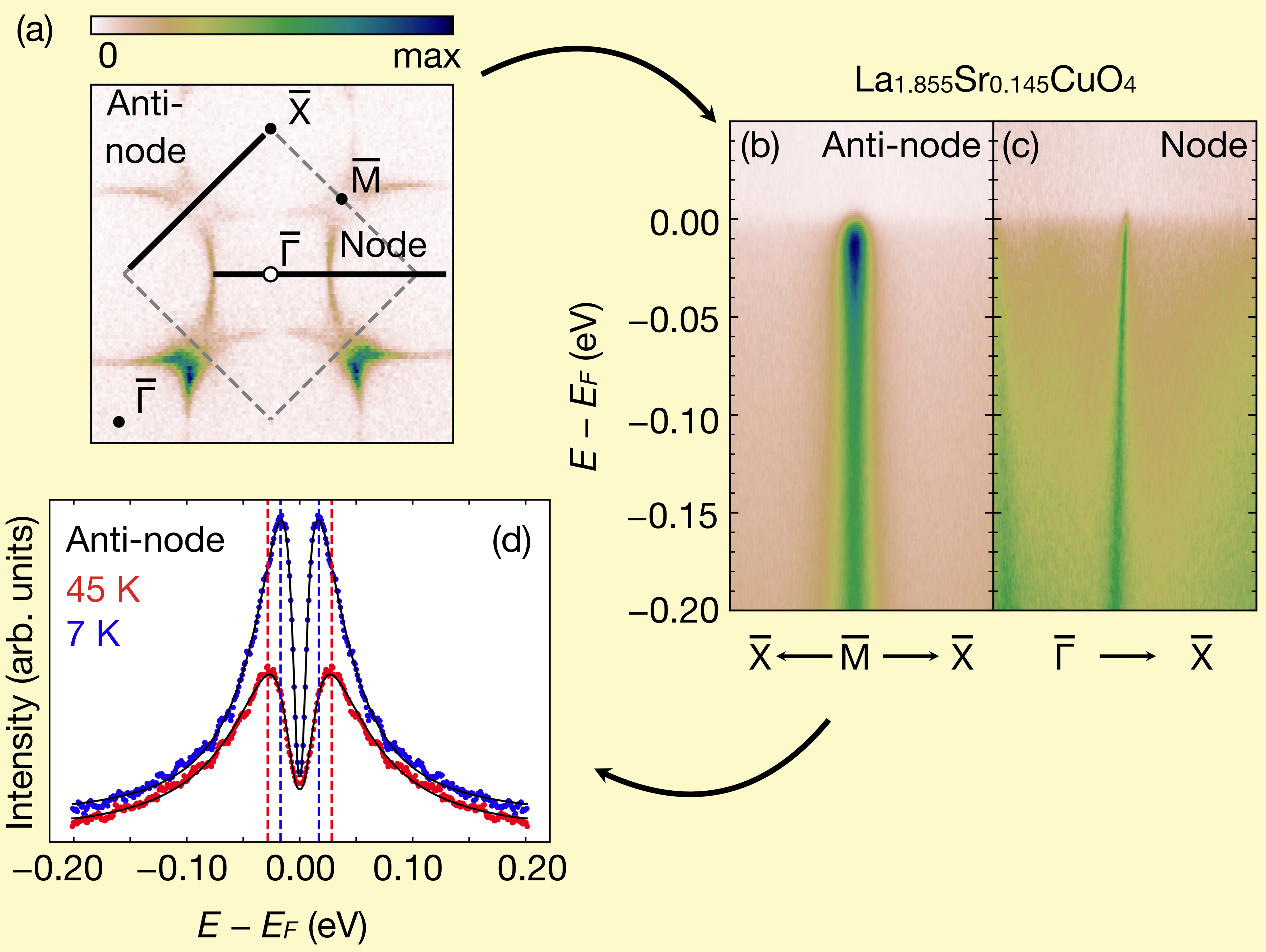


Fig.: (a) Crystal structure of $PrNiO_2$ and scattering geometry of the RIXS experiment. (b) Intensity map of magnon excitations. The inset shows the trajectory in momentum space of the RIXS measurements. (c) Spectra of the $PrNiO_2$ film grown on various substrates. (d) Experimental team (Qisi, Pascal, Roger, Annabella, Iza) in front of the RIXS spectrometer at the DIAMOND synchrotron.

[1] Q. Gao *et al.*, Magnetic Excitations in Strained Infinite-layer Nickelate $PrNiO_2$, arXiv:2208.05614 (2022)

Electronic band structure - ARPES



How does the electronic dispersion look like?

Example:

- Extracting the gap below and above the superconducting transition temperature in La-based cuprates
- Superconductivity suppresses pseudogap

[3] J. Küspert et al., Pseudogap suppression by competition with superconductivity in La-based cuprates, Physical Review Research 4, 043015 (2022)

Deep-Learning Based Approach for Denoising Diffraction Data

We utilize new advances in the field of deep learning and show that by training a deep convolutional neural network we are able to strongly enhance weak signals (such as charge-density-wave signals) in noisy X-ray diffraction data. This success is enabled by supervised training with pairs of measured low- and high-noise data. This way, the neural network learns about the statistical properties of the noise, can successfully remove it and reveal the underlying intrinsic features of the signal.

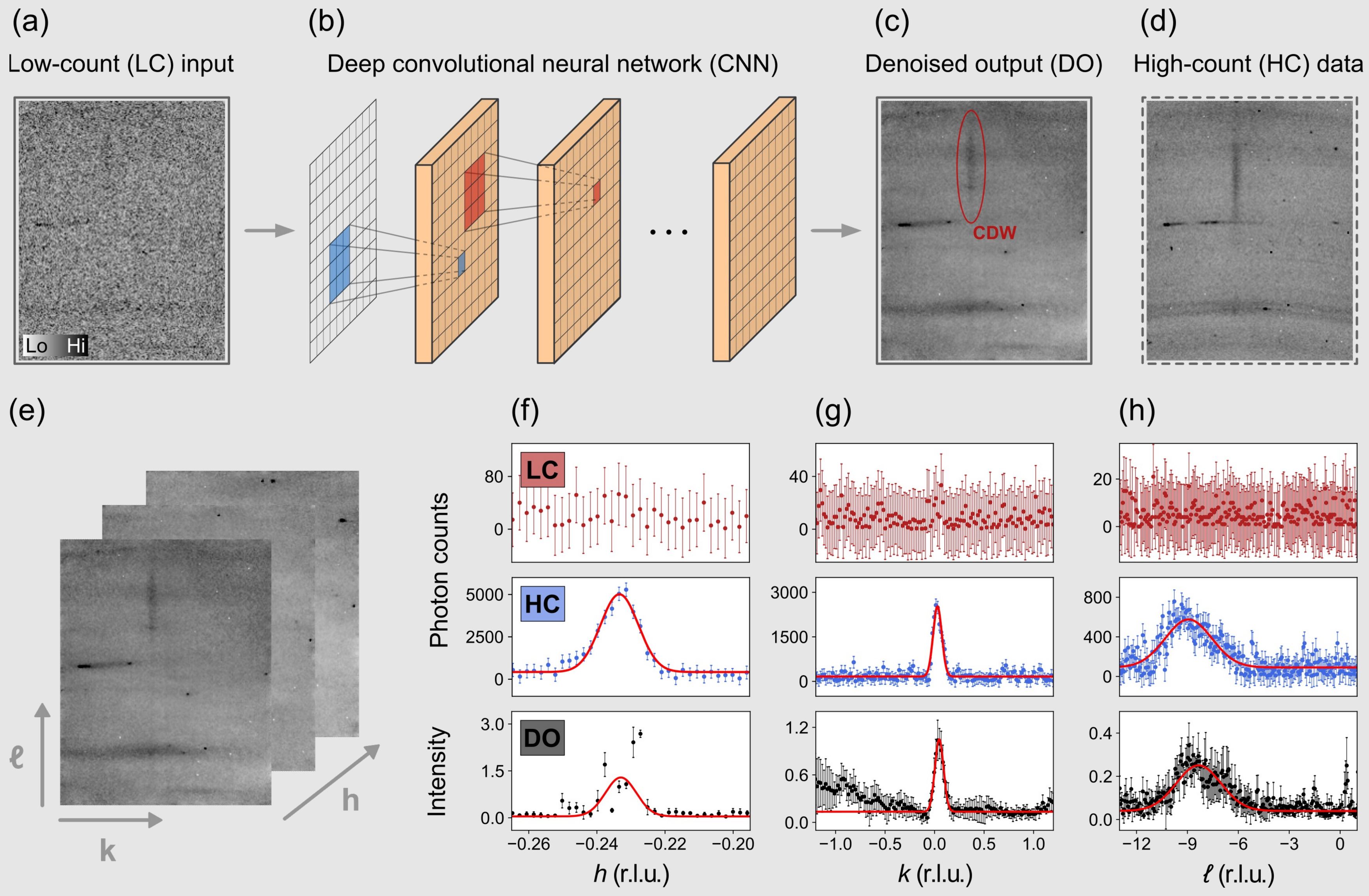
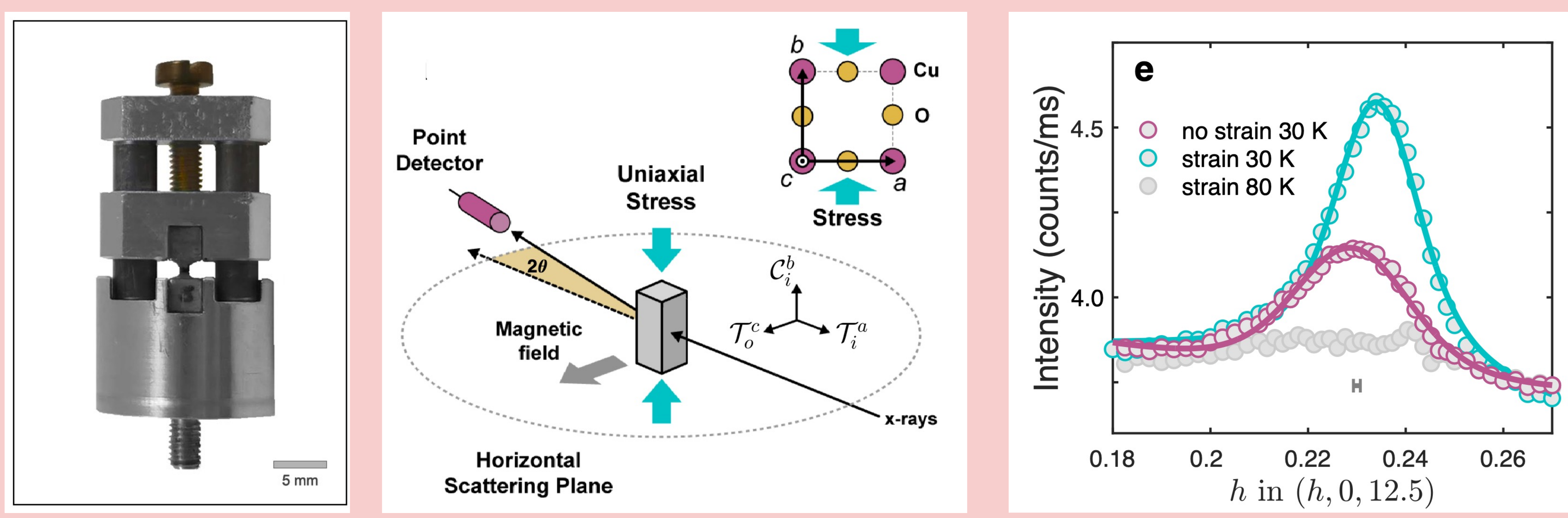
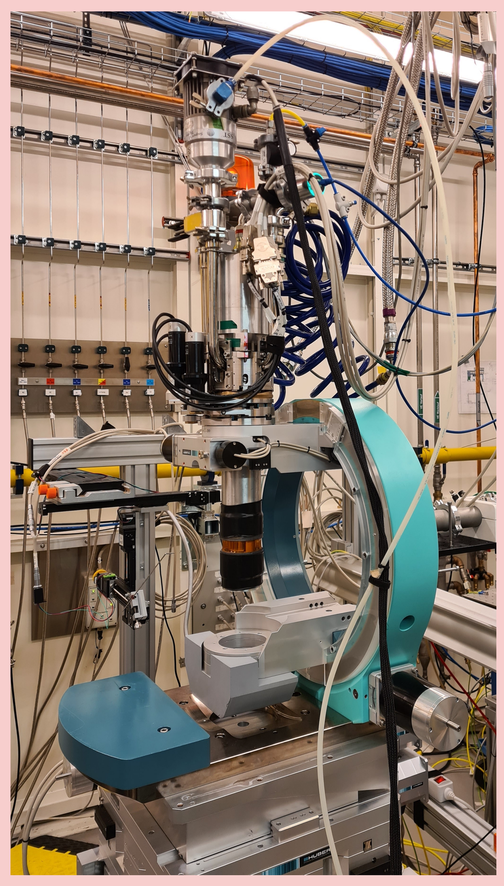


Fig.: Example of denoising X-ray diffraction data using a deep convolutional neural network (CNN). (a-c) A trained deep CNN produces a denoised version of a real experimental low-count frame. (d) The real experimental high-count frame is shown for comparison. (e) A stack of denoised X-ray intensity frames as in (c). (f-h) One-dimensional projected scans through $Q \approx (0.23, 0, 8.5)$ along the h, k and ℓ reciprocal space axes demonstrate the effectiveness of the trained neural network.

[2] J. Oppliger et al., Weak-Signal Extraction Enabled by Deep-Neural-Network Denoising of Diffraction Data, arXiv:2209.09247 (2022)

Charge Order - XRD





How to resolve the lattice structure?

We mostly measure Bragg peaks and charge order (periodic modulation of charge) peaks.

Some questions we address(ed):

- How does a $La_{2-x}Sr_xCuO_4$ crystal react to the application of uniaxial stress along the Cu-O direction?
- How can we influence the interplay between charge order and superconductivity by strain, magnetic field and temperature?

[4] J. Choi et al., Unveiling Unequivocal Charge Stripe Order in a Prototypical Cuprate Super-conductor, Physical Review Letters 128, 207002 (2022)