Inverse Problems and Image Reconstruction in Medical and Industrial Imaging

and Bringing AI Knowledge to Austrian Companies

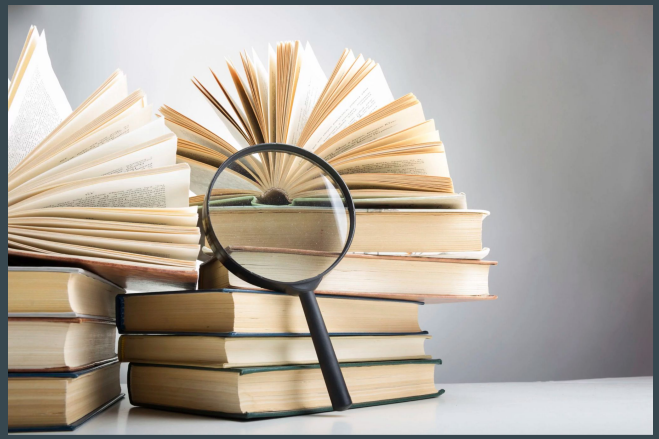
Nadja Gruber, University of Innsbruck & AI Factory,
Make it (net)work! - MLA2S Networking Seminar

About my Research

2019 — 2024: PhD in Applied Mathematics with a focus in medical image segmentation, denoising and reconstruction (supervisor: Prof. Markus Haltmeier)

2024 – 2025: PostDoc at Digital Cardiology Lab (focussing on classification of microvascular injuries from ECG using foundation models)

since October 2025: Senior Scientist/Lecturer at the LFU (Department of Computer Science, QE group lead by Prof. Ruth Breu)



Overview of the Talk...

I will give an overview of:

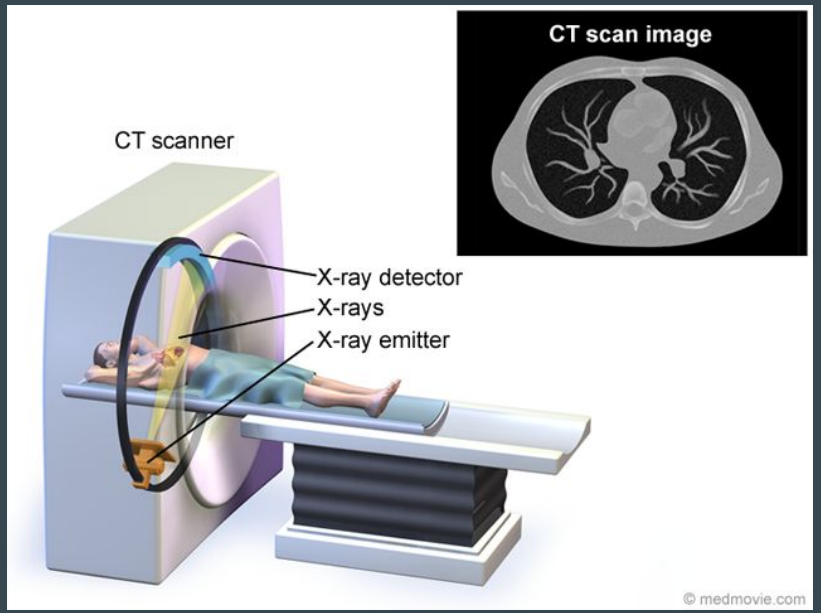
- Self-supervised CT reconstruction
  - Introduction to splitting-based self-supervised learning
  - Method development and design choices
  - Results and evaluation
  - Applications in X-ray CT, neutron CT and cryo-electron tomography
  - Current challenges and future research
- From AI Research to University Continuing Education
  - FFG Qualification Project with industry partners
  - Upcoming uWINs: Short, practice-oriented AI courses
  - New university continuing education programme: Data, Software and AI

Self-supervised Learning for CT Reconstruction



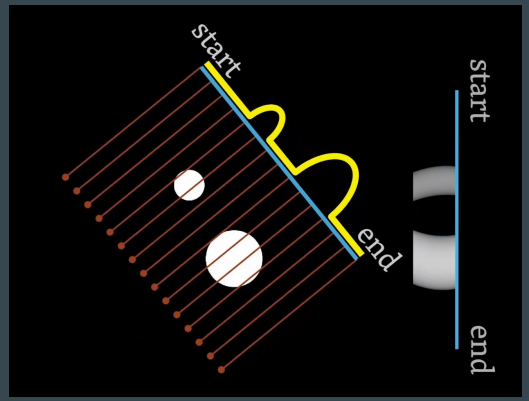
What is Computed Tomography?

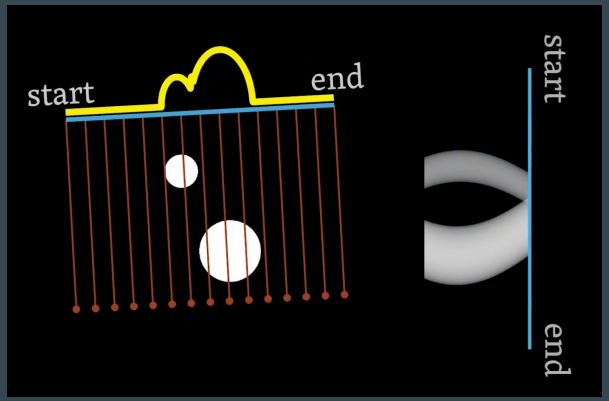
- An X-ray tube rotates around the patient
- Detectors in the gantry measure how much X-rays are attenuated by different tissues
- Multiple X-ray projections are acquired from many angles
- The collected data are processed using **reconstruction algorithms**

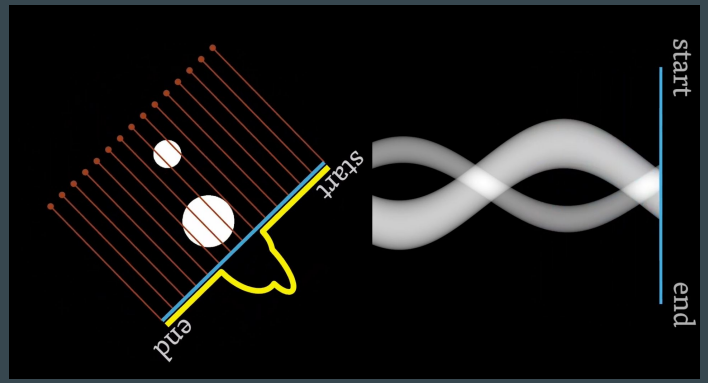


https://medmovie.com/library_id/3255/topic/ahaw_0230i/

What is Computed Tomography?

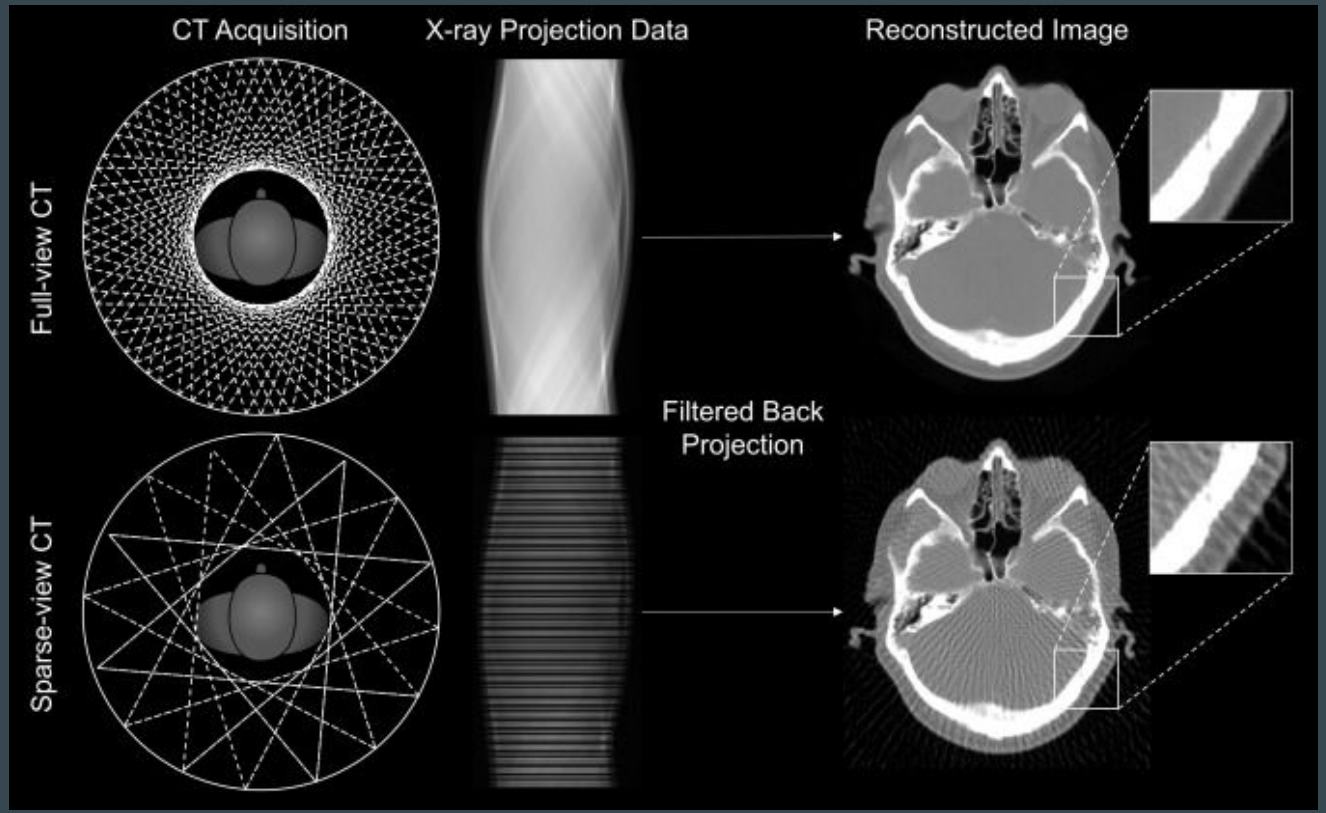






Source: How X-ray sinogram builds up, https://www.youtube.com/watch?v=LS4C7-GE_zE

Less radiation - worse images! :(



Chung, Kevin J., et al. "Low-dose CT perfusion with sparse-view filtered back projection in acute ischemic stroke." Academic Radiology 29.10 (2022): 1502-1511.

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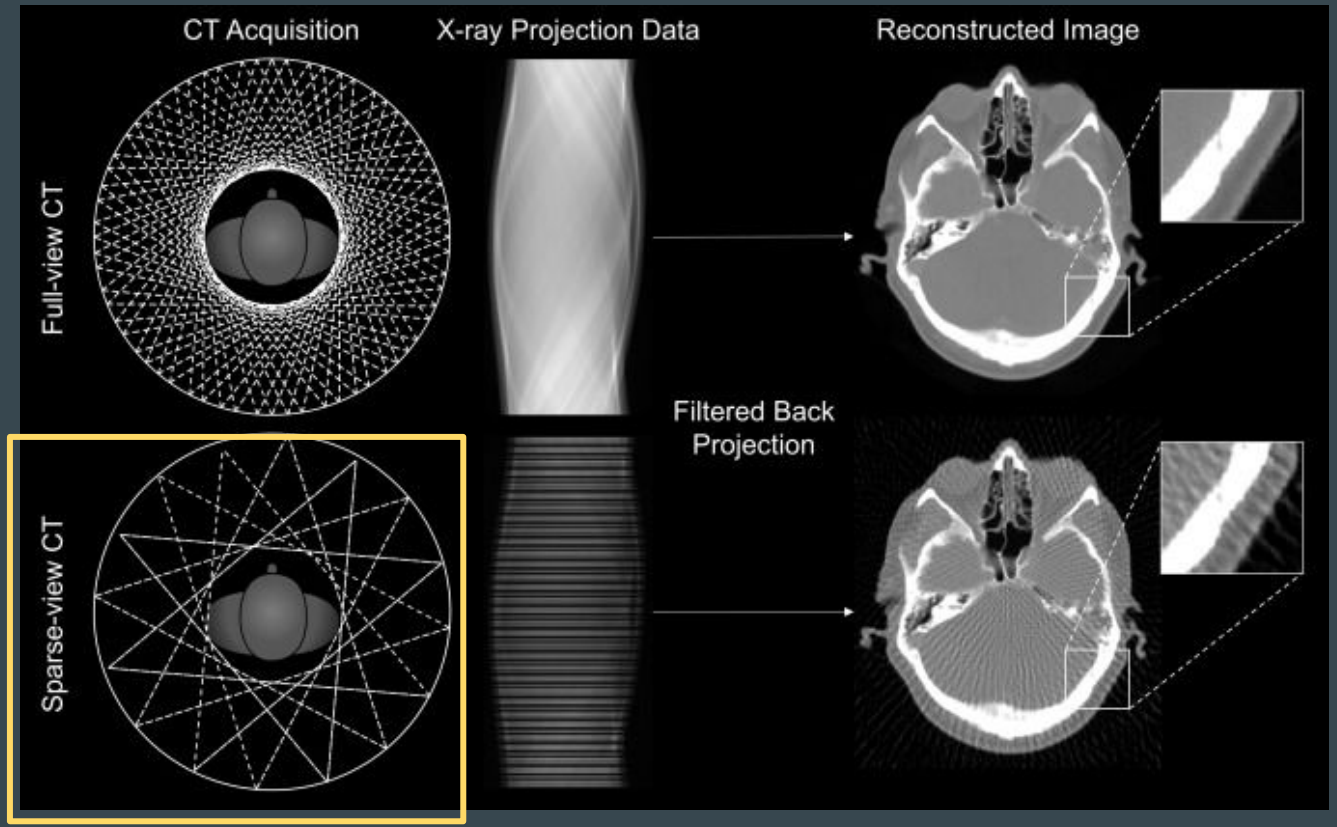

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Challenges in Sparse-View Image Reconstruction

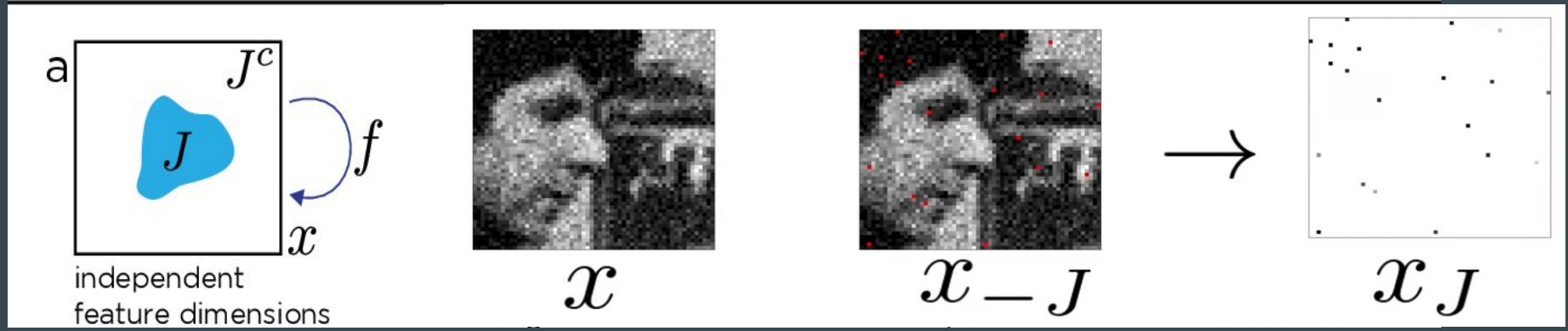
- Streak artifacts
- Noise and Blur
- Ill-posedness: reconstruction system underdetermined (‘less equations than unknowns’)
  -> many solutions can satisfy sparse data



Existing Reconstruction Methods

- Traditional mathematical methods:
  - Filtered backprojection, iterative reconstruction
  - Pros: Interpretable, grounded theory
  - Cons: limited performance
- Supervised learning:
  - learns mapping from degraded to high quality images using CLEAN data
  - Pros: high performance
  - Cons: Requirement of large paired datasets
- **Self-Supervised Learning :**
  - **Learns from unlabeled data**
  - **Uses masking or synthetic degradation**
  - **Pros: no need for ground truth data**
  - **Cons: Sometimes slightly lower performance than supervised methods**

The concepts of self-supervised Denoising- Noise2Self



Assumption: noise is independent, signal has structure

Idea: Predict from neighbors -> learn signal, not noise!

Source: Noise2Self: Blind Denoising by Self-Supervision, Batson, 2019

The concepts of self-supervised Denoising- Noisier2Noise

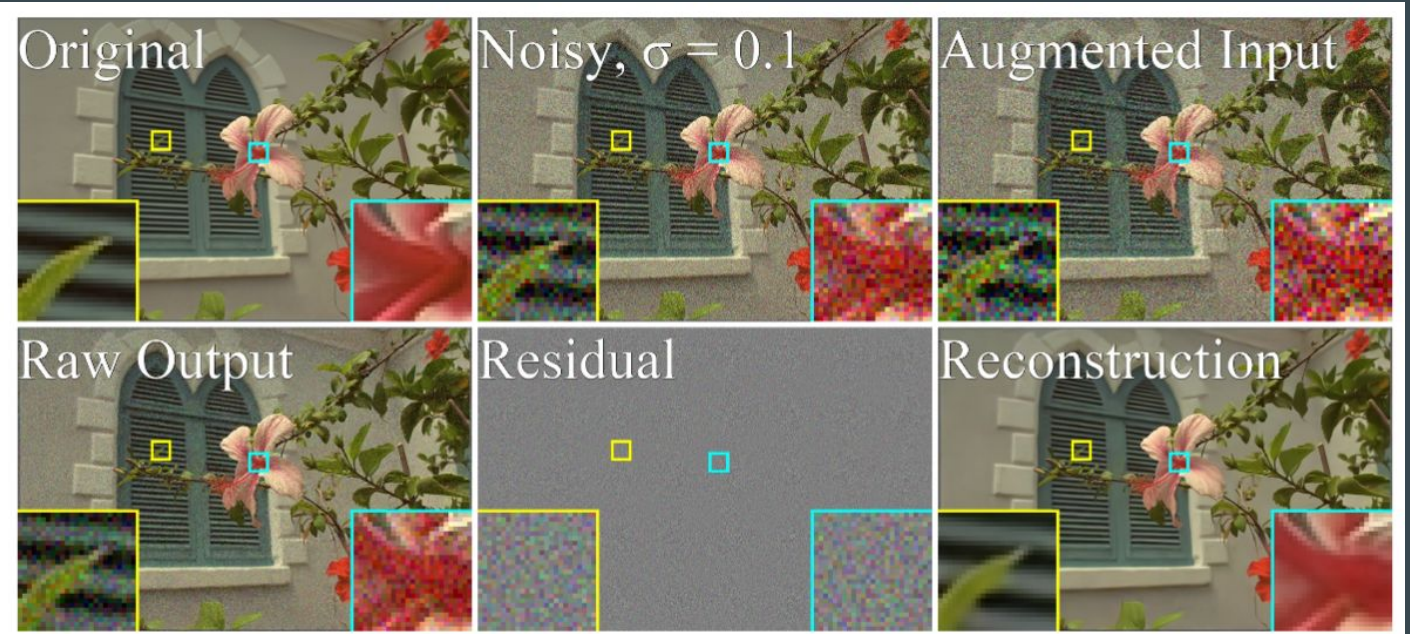
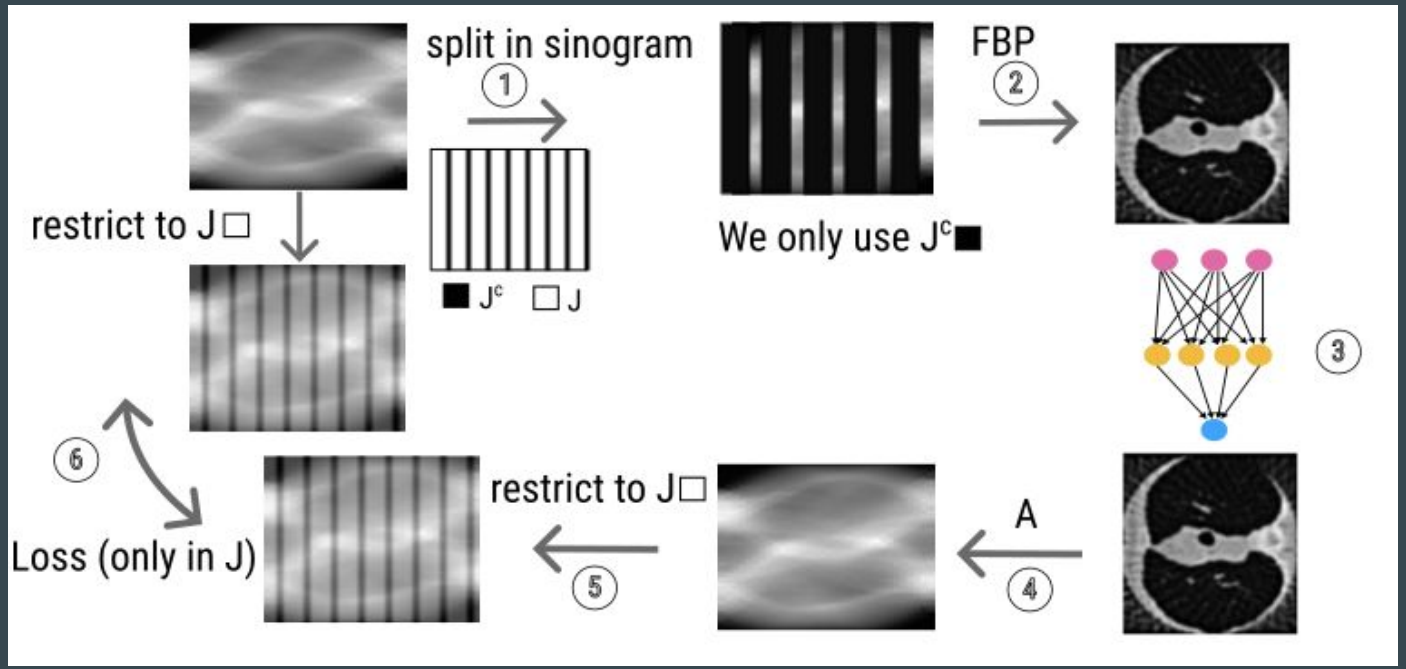


Figure 2. The steps of our method with $\sigma = 0.1$. Top Row: Original clean image (unseen by our method), a singly-noisy realization (which is our training target), a doubly-noisy realization (which is the input to our network). Bottom Row: The raw output of our network, the implicit estimate of the remaining noise, and the final reconstruction after our correction step.

Source: Noisier2Noise: Learning to Denoise from Unpaired Noise Data, Moran, 2019

Our proposed approaches

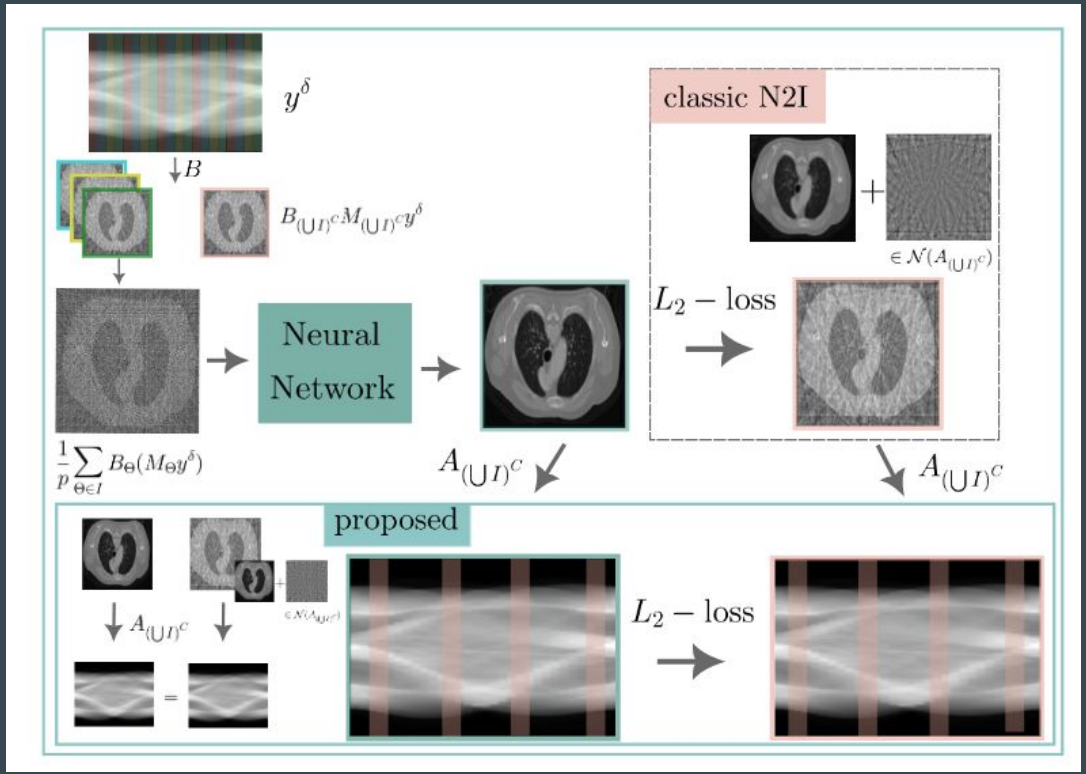
How can Noise2Self Idea be used for Reconstruction?



Sparse2Inverse*

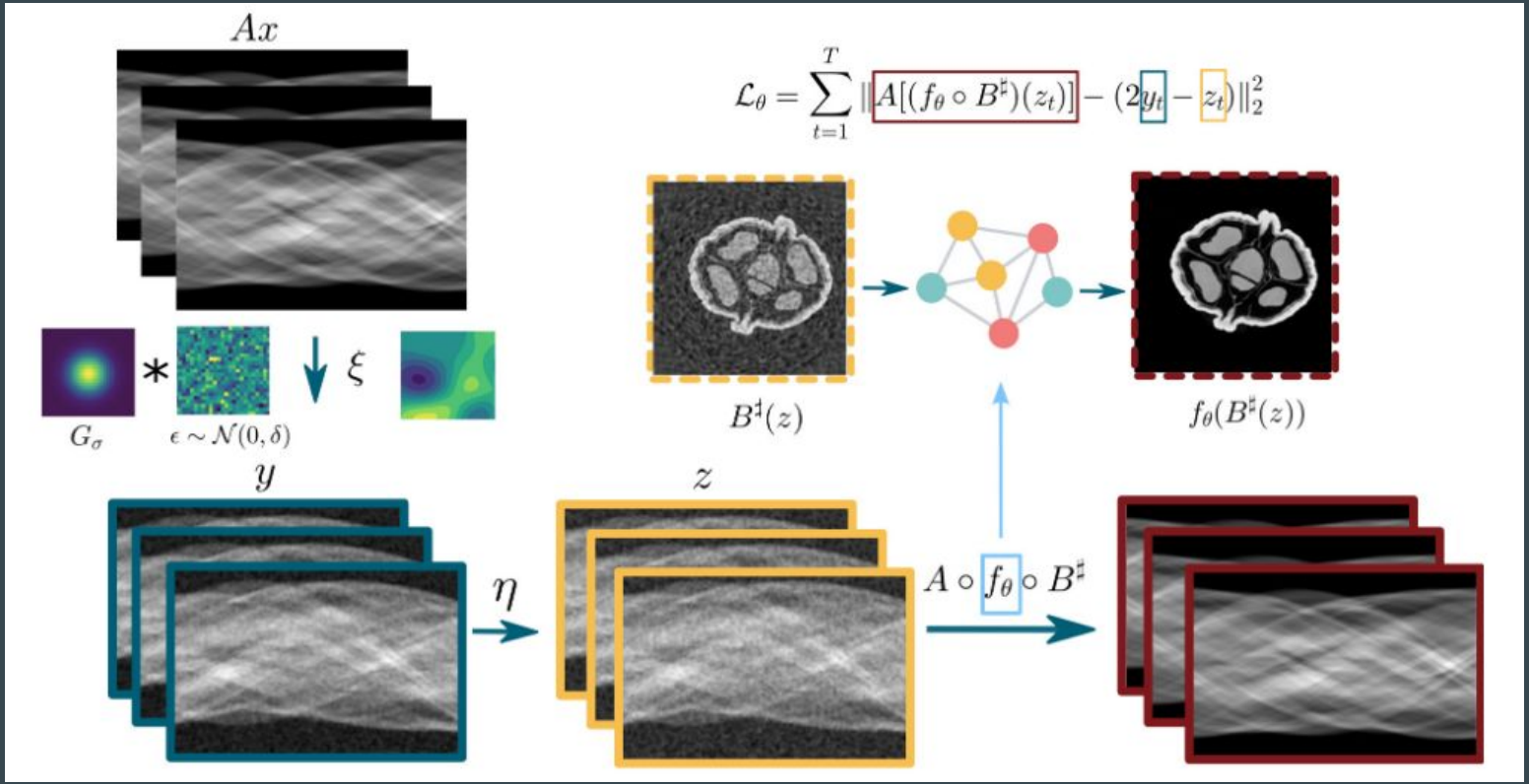
Idea: Neural Networks prefer ‘simple structures’

- Split data in sinogram
- Reconstruct (FBP) from data NOT in J
- Train neural network in reconstruction domain
- Apply A (forward map)
- measure loss in data domain only on pixels inside J



*Gruber, N., Schwab, J., Gizewski, E., & Haltmeier, M. (2024). Sparse2Inverse: Self-supervised inversion of sparse-view CT data. arXiv preprint arXiv:2402.16921.

Noisier2Inverse*



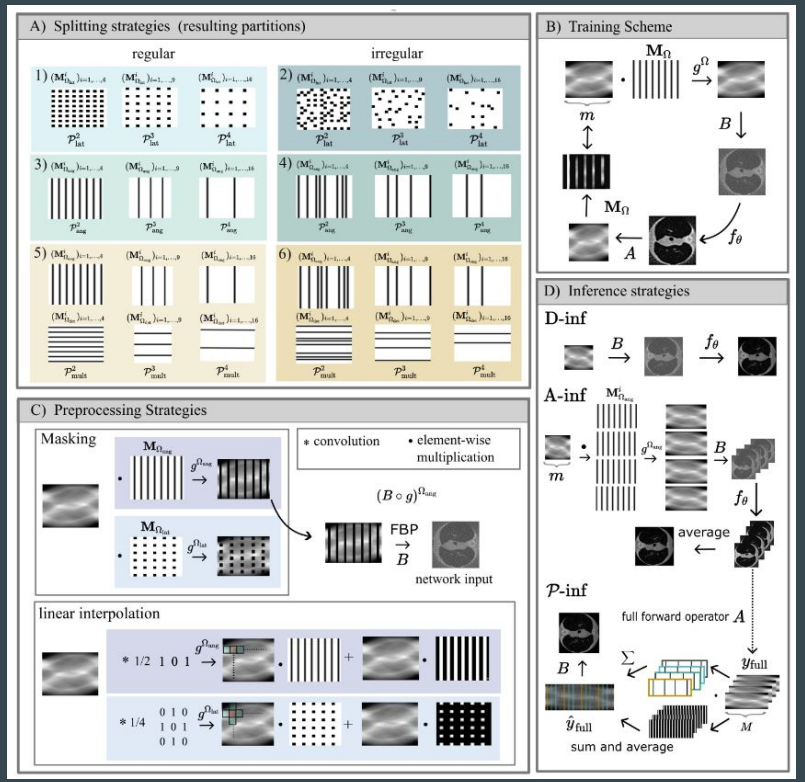
*Gruber, N., Schwab, J., Haltmeier, M., Biguri, A., Dlaska, C., & Hwang, G. (2025). Noisier2inverse: Self-supervised learning for image reconstruction with correlated noise. IEEE Access.


Understanding and analyzing the ingredients of splitting based approaches

Design Choices in Splitting-Based Self-Supervised Sparse-View CT Reconstruction

This project tries to answer several questions relevant for scientists working in the applied field:

- What is an efficient way of splitting the data in CT?
- What inference should be used?
- How should the data be processed?
- When to stop training if no ground truth is available?

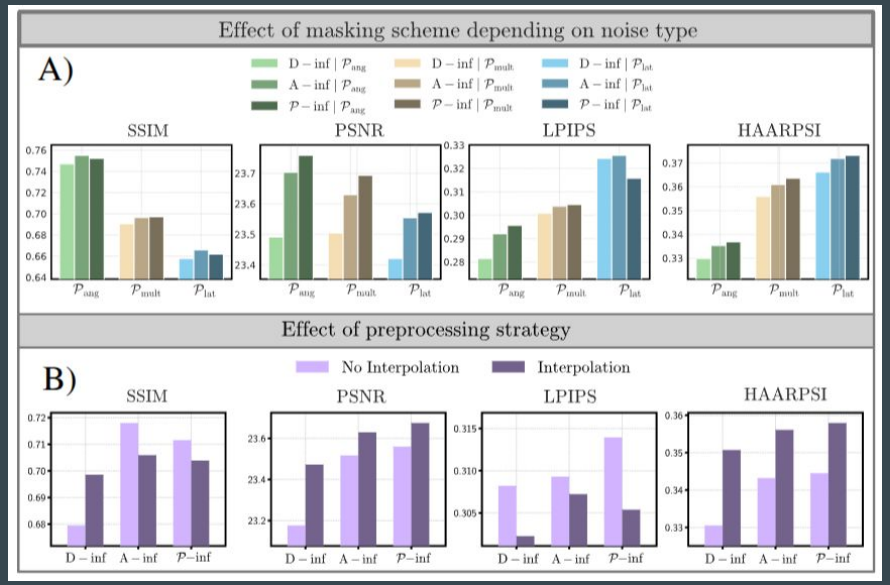


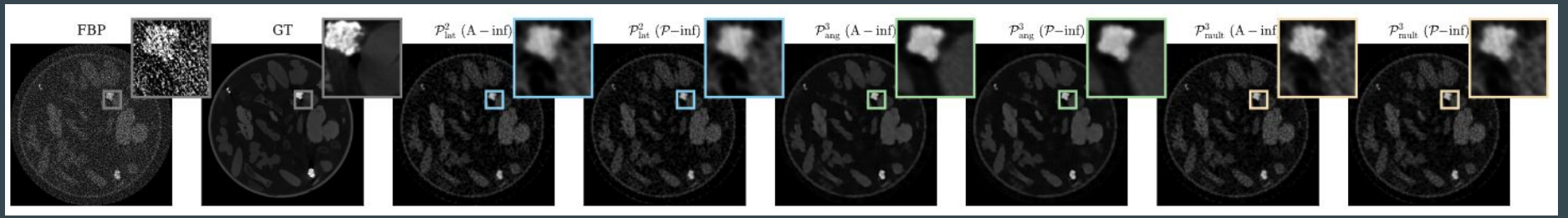
Design Choices in Splitting-Based Self-Supervised Sparse-View CT Reconstruction, N.Gruber, M. Haltmeier, L.Neumann, G.Hwang, J.Schwab (submitted)

Observations and future work

Key observations:

- **No universally optimal splitting strategy:** Reconstruction quality depends on the measurement characteristics.
- **Noise structure matters:** Lattice-based splitting performs well with independent noise, while angular splitting is more robust to correlated noise.
- **Multi-partition splitting** can **improve** reconstruction quality compared with purely projection-wise splitting.
- **Evaluation matters:** Differences in structural and perceptual quality are not always reflected by PSNR and SSIM.







Modelling real-world noise

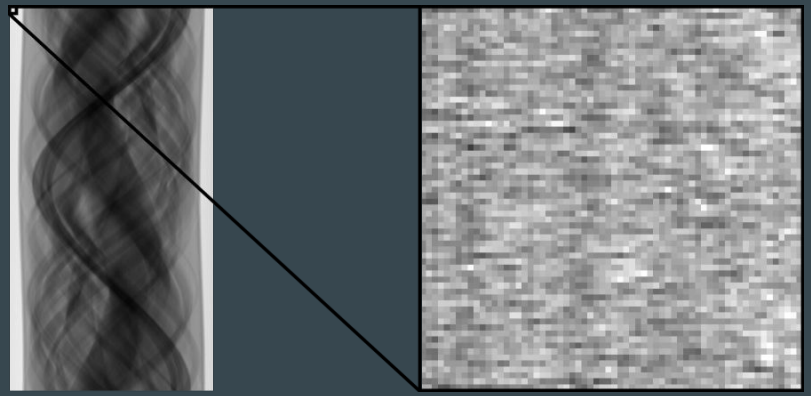
What about real-world data?

Current Project (early stage career funding): Existing methods use ‘idealized’, unrealistic assumptions about the noise.

In Reality:

- Scintillator blur
- Signal dependent correlated Poisson component + Gaussian noise

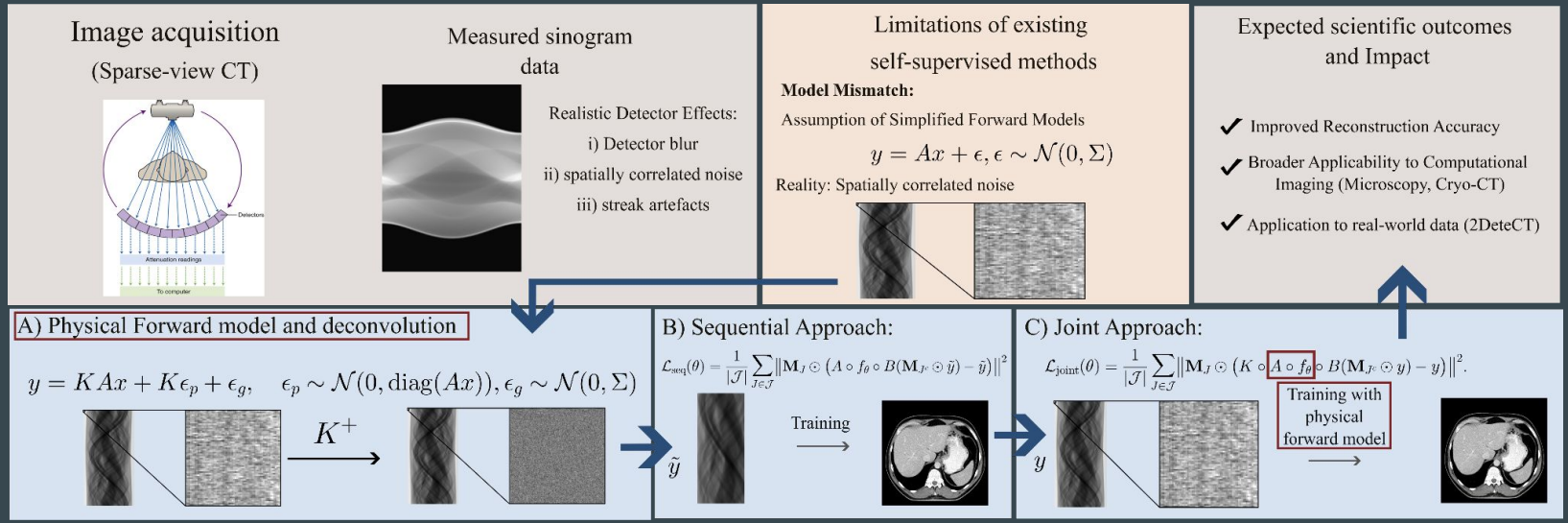
Integration of physical model in training process (in collaboration with A. Martinez (Master student, University of Valencia), J. Schwab (Hochschule Kufstein), A. Graas (Delft University) and A. Biguri (Cambridge Image Analysis group))

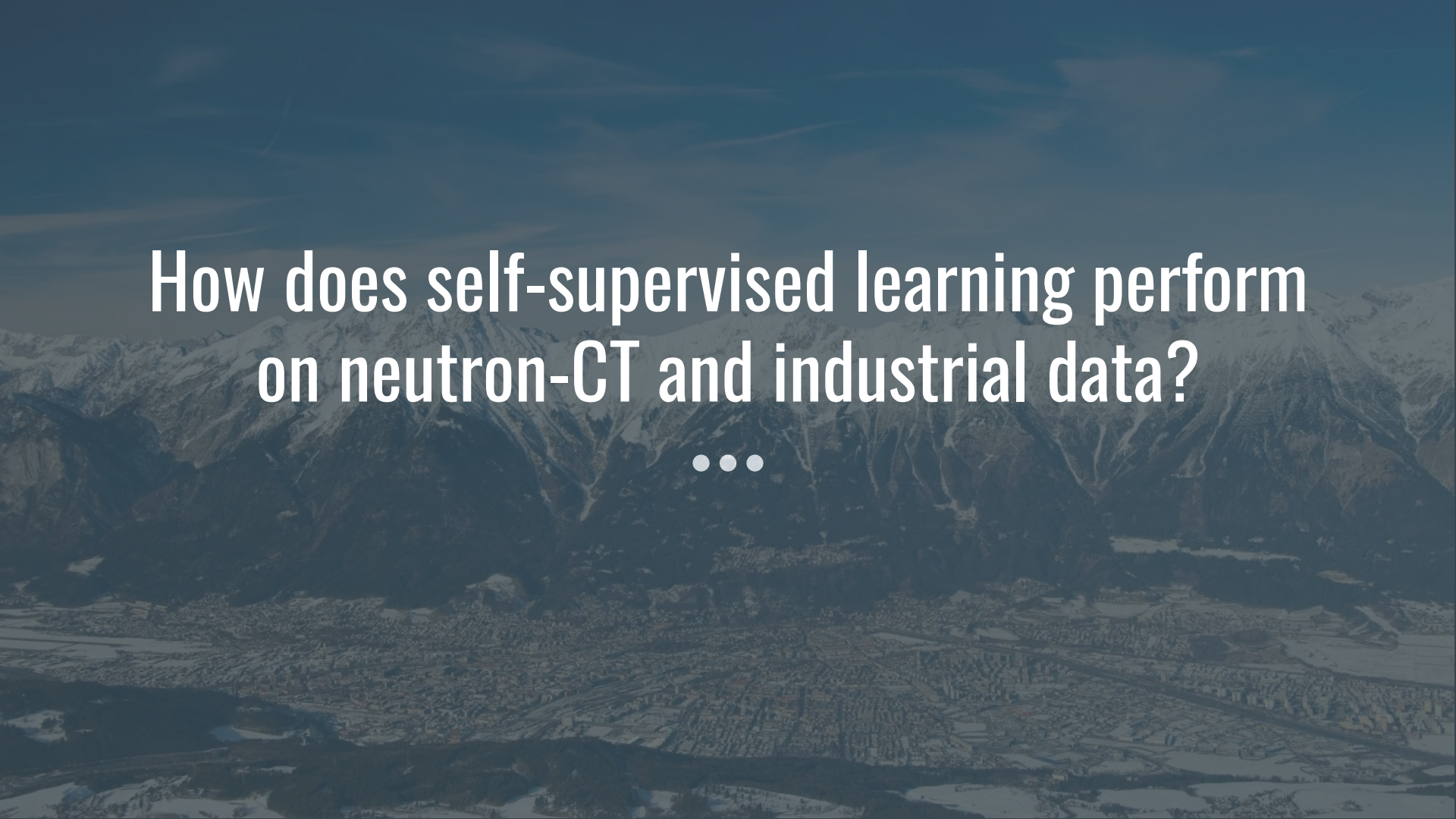


Schut, Dirk Elias, et al. "Equivariance2Inverse: A Practical Self-Supervised CT Reconstruction Method Benchmarked on Real, Limited-Angle, and Blurred Data." IEEE Transactions on Computational Imaging (2025).

Research Plan

- The problem: Real CT measurements are affected by detector blur and spatially correlated noise.
- Physical modelling: Incorporate realistic detector effects into the reconstruction process.
- Sequential approach: Correct the measurements first, then train the reconstruction network.
- Joint approach: Integrate the physical forward model directly into self-supervised training.




How does self-supervised learning perform on neutron-CT and industrial data?
...

Application II: Neutron CT reconstruction

- A **neutron beam** passes through the sample while the sample rotates.
- Detectors measure how neutrons are transmitted, absorbed, or scattered by different materials.
- Unlike X-rays, neutrons interact with atomic nuclei, providing a different contrast mechanism.
- Hydrogen-rich materials strongly attenuate neutrons, while many metals allow neutrons to pass through with relatively little attenuation.

Applications: Non-destructive imaging in materials science, engineering, battery research, and cultural heritage.

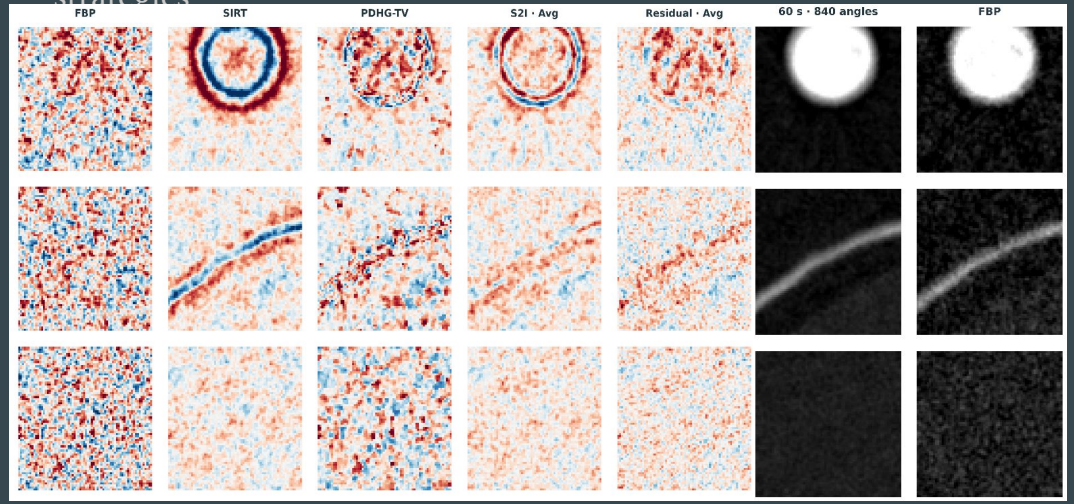
UKRI Science and Technology Facilities Council

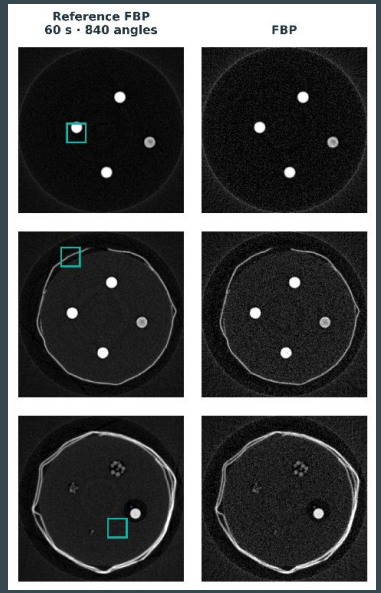
ISIS Neutron and Muon Source



Project Goals

- **Reduction of radiation time while preserving reconstruction quality**
- Benchmarking of Self-supervised approaches on Neutron-CT data vs classical approaches (parameter tuning is required, usually slower)
- Address weaknesses of S2I and co by developing detail-preserving strategies





FBP Reconstructions on 15 s data of aluminium cylinder, scanned at IMAT, experiment number RB2480001.

Collaborators



Sylvia Britto, IMAT



Edoardo Pasca, CCPI



Margaret Duff, STFC

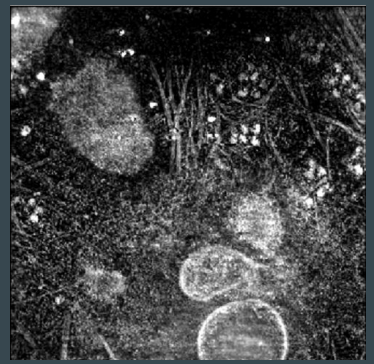
Tiny Structures, Big Reconstruction Challenges

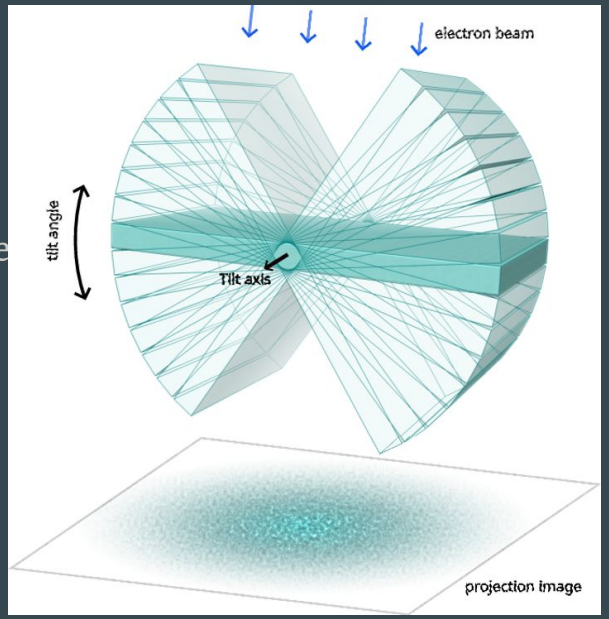


Future Work: Integrating self-supervised learning to Cryo-ET Reconstruction

Challenges

- Extreme noise
- Missing wedge and CTF leave Fourier gaps
- Geometry only approximately known pe tilt
- The forward model couples all of these together





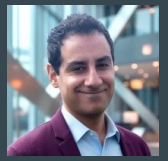
bi[o]hub

University of Applied Sciences
Hochschule
Kufstein Tirol



Johannes Schwab, HOK

Project Leader



Dari Kimanius,

Biohub



Ronquing Chen-Christopher, HOK

From Promising Reconstructions to Trustworthy Imaging

Key Takeaways

- Self-supervised learning enables image reconstruction without clean reference images.
- Reconstruction quality depends on the m**easurement characteristics, noise structure, and data-splitting strategy.**
- Realistic modelling of the imaging process is **essential** for transferring methods to **real-world** applications.

Open Research Questions

- How can we ensure reliable reconstructions **without** ground truth?
- How can we preserve **fine details while avoiding artificial structures?**
- How can we generalize self-supervised approaches across imaging modalities such as X-ray CT, neutron CT, and cryo-ET?

From Research to Practice: AI Education

FFG Qualification Project: AI Skills for Industry



- Funded qualification project with **nine** Tyrolean companies
- University of Innsbruck develops tailored AI training
- Focus on concrete needs in industrial practice: understanding the basics of AI, Prompt engineering, LLM-Finetuning, building n8n workflows,..
- Four in-house Workshops followed by individual bootcamps tailored to the companies needs



Prof. Ruth Breu



Benedikt Dornauer

Senior Lecturer/Scientist

FFG
Forschung wirkt.



ADLER
WALDHART SOFTWARE
hollu
GUTMANN
Hier versorgen wir.
AVAHLE
PFEIFER
TINETZ
General Solutions
SOFTWARE

uWINs: Compact AI Training (starting in February)



AI in Everyday Work

uWIN
Generative AI as a Work Partner

Fundamentals & Practical Use

- ✓ Use and understand AI assistants
- ✓ Improve workflows with effective prompting
- ✓ Apply relevant EU AI Act requirements

uWIN
Automation with AI Agents

Building Workflows with n8n

- ✓ Understand what AI agents can do
- ✓ Build n8n workflows with LLMs, tools and data
- ✓ Automate a real workplace use case

Data & ML in Industry

uWIN
Understanding & Visualising Data

From Raw Data to Insights

- ✓ Clean and structure industrial data
- ✓ Create insightful visualisations and dashboards
- ✓ Use data to inform decisions

uWIN
Machine Learning in Industry

Data Analysis & Process Optimisation

- ✓ Explore predictive maintenance and quality control
- ✓ Train ML models on real industrial data
- ✓ Improve industrial processes

University program: ‘Daten, Software und KI’



Michael Vierhauser

Assistant Prof.

Build Expertise – Develop Professional Roles

Build skills in data, software and AI to prepare professionals for emerging roles.

Explore Ideas – Put Them into Practice

Identify opportunities for digital products, processes and services and implement them in practical projects.

Strengthen Companies – Enable Transformation

Support companies through continuing education in digital transformation, automation and new business models.



Software Engineering



Data Science, ML

University program: ‘Daten, Software und KI’



Five modules, 60 ECTS in total

Module I	Module II	Module III	Module IV	Module V
Programming and AI-assisted development	Data-driven learning and AI	Software Engineering project	Advanced software and data science	Supervised application project
10 ECTS	10 ECTS	10 ECTS	10 ECTS	20 ECTS

Flexible pathways

Individual modules

Module II or IV (10 ECTS)

Shorter program

Modules I–III (30 ECTS)

Full program

All five modules (60 ECTS)

Flexible, part-time and project-oriented continuing education

AI Factory Austria

Training and Knowledge Transfer



Team West



Ruth Breu



Radu Prodan

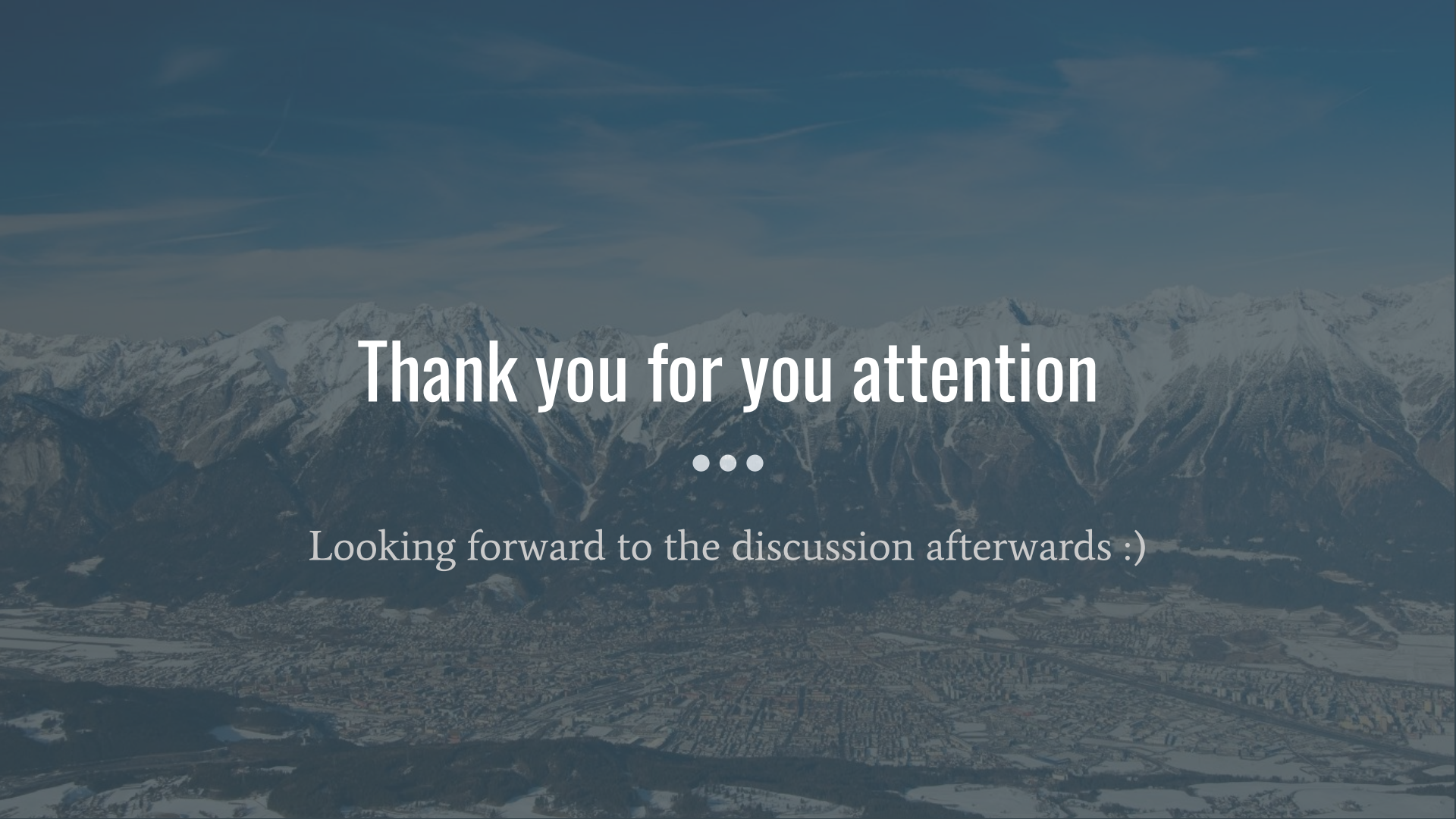


Julian Just

Training opportunities and practical AI support

ai-at.eu/trainings/

EuroHPC Joint Undertaking
Funded by the European Union
Federal Ministry Innovation, Mobility and Infrastructure Republic of Austria



Thank you for you attention

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Looking forward to the discussion afterwards :)