On the Impact of Input Feature Selection in Deep Scatter Estimation for Positron Emission Tomography

Yannick Berker and Marc Kachelrieß

German Cancer Research Center (DKFZ), Heidelberg, Germany

DEUTSCHES
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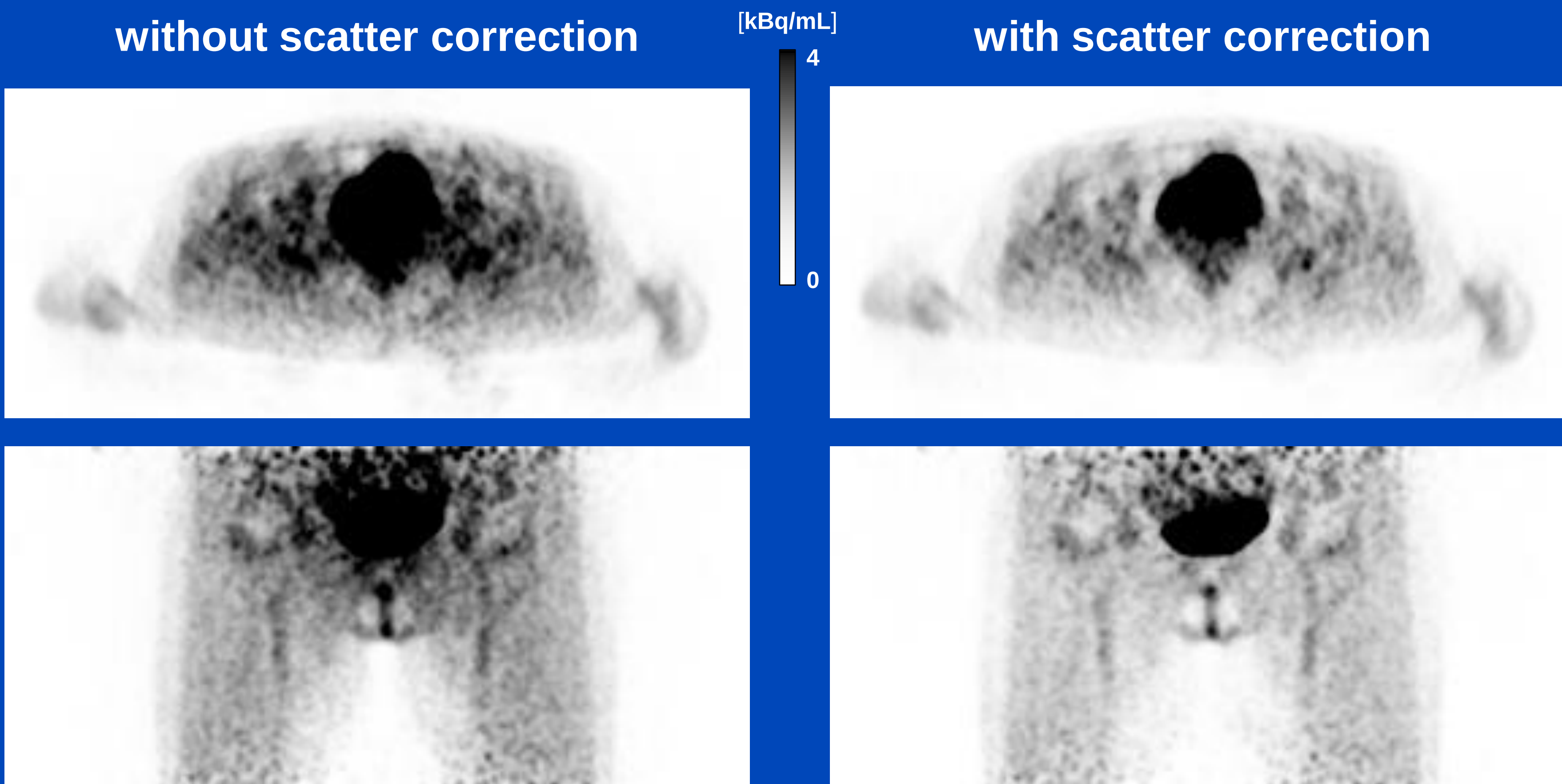
IN DER HELMHOLTZ-GEMEINSCHAFT

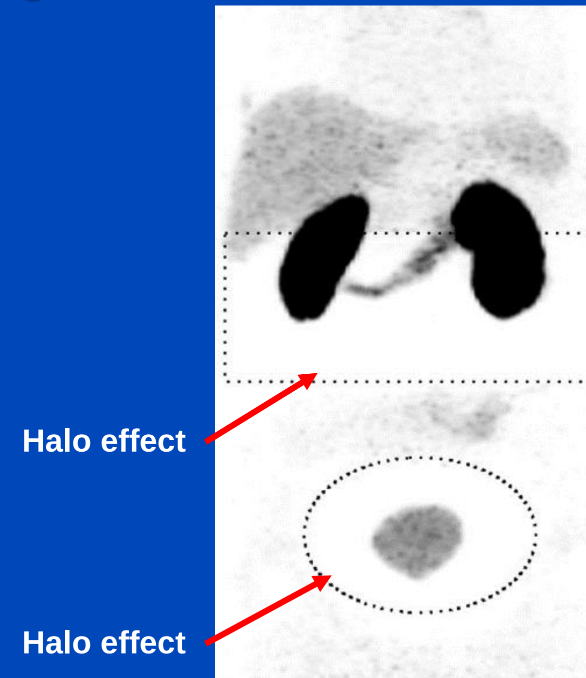
PET Scatter Correction

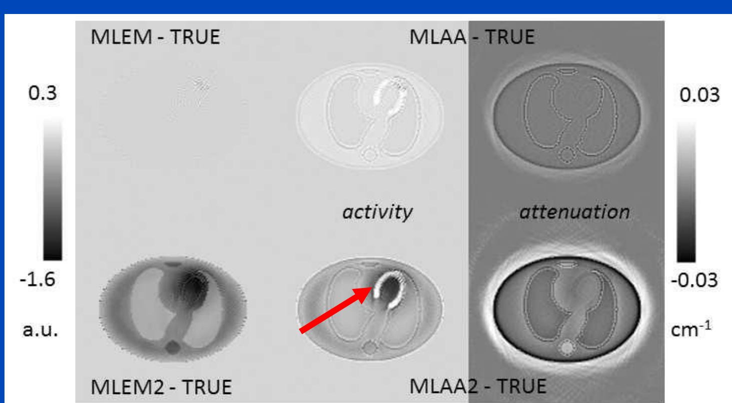


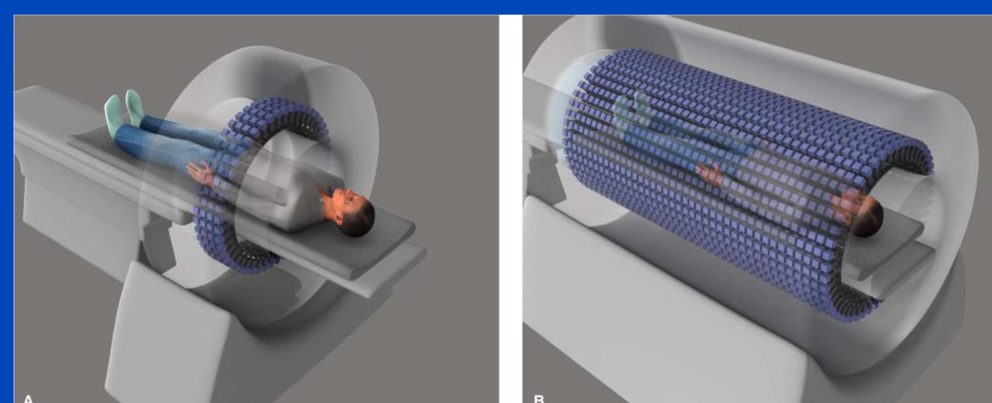
→ **improved contrast**
→ **improved lesion detectability**
→ **better quantification**

Scatter-Sensitive PET Applications

- **Highly-specific PET tracers[1]**
  - **Halo effect with ^{68}Ga-PSMA**
- **Joint estimation[2,3]**
  - **Unknown radiotracer and attenuation**
- **Long-axial-FOV PET scanners[4]**
  - **Need for fast whole-body scatter simulation**







[1] Heußer, Kachelrieß et al. *PLoS ONE*. 2017;12(8):e0183329.
[2] Heußer, Kachelrieß et al. *IEEE Trans Nucl Sci*. 2016;63(5):2443-51.
[3] Nuyts et al. *IEEE TRPMS*. 2018;2(4):273-8.
[4] Cherry et al. *Sci Transl Med*. 2017;9(381):eaaf6169.

Motivation

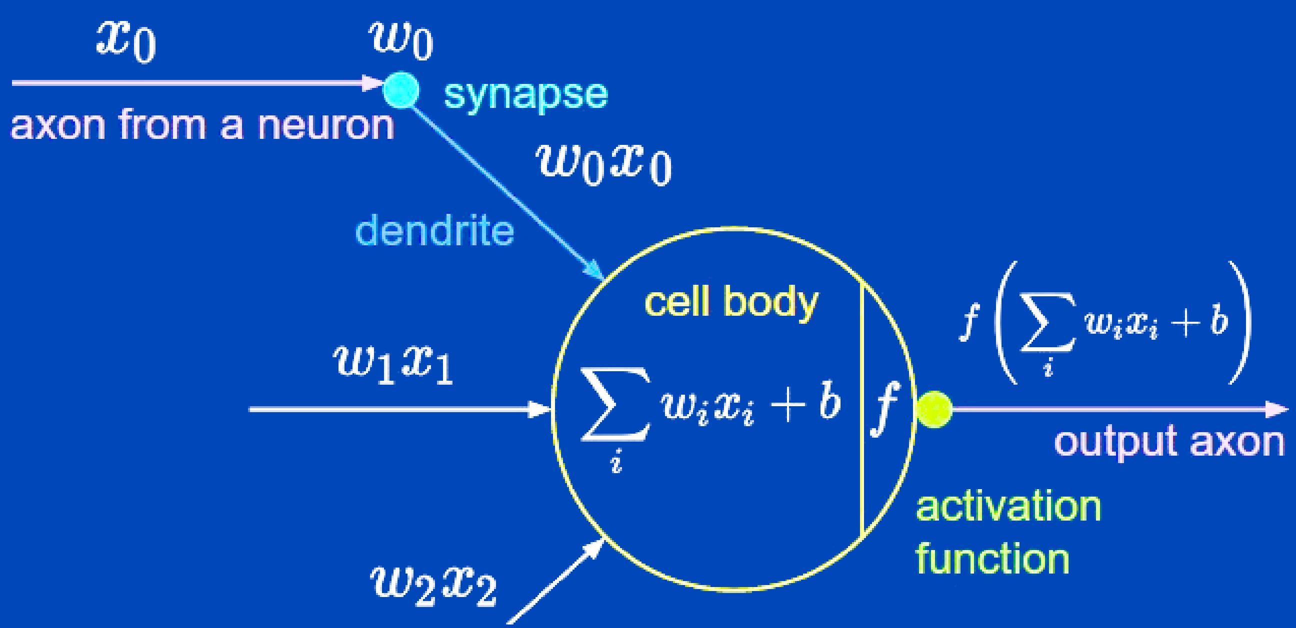
- **Monte Carlo scatter simulation (MCSS)**
  - Highly accurate
  - Slow (computationally expensive)
- **State of the art: Single scatter simulation (SSS)**
  - Relatively fast
  - Inaccurate (tail fitting)

➢ **Objective** Fast (and accurate) scatter correction

➢ **Approach** Convolutional Neural Networks (CNNs)
  - SSS-based: speed-up of (TOF-)SSS still subject of research[1]
  - Aim: MC-based deep scatter estimation

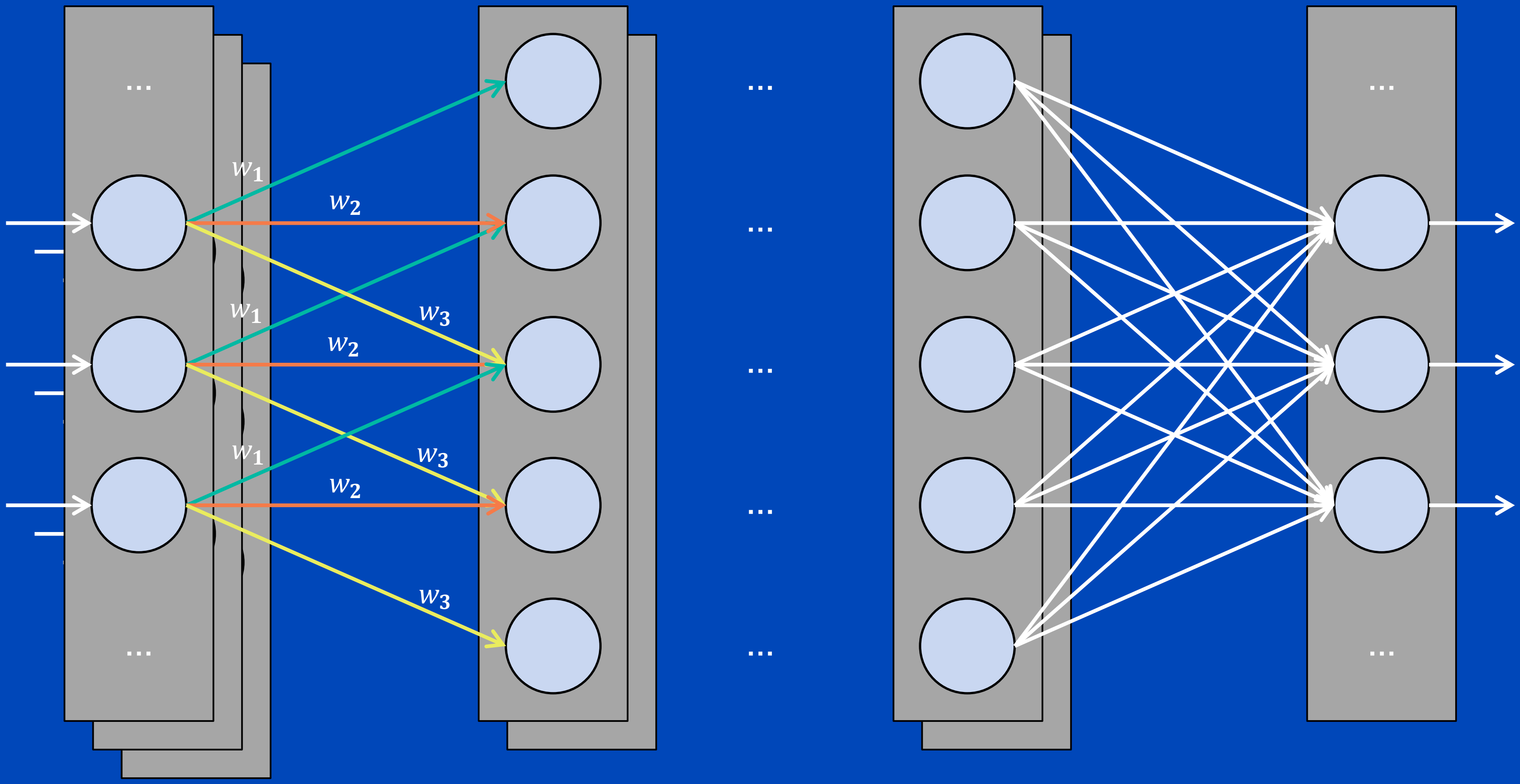
[1] Nikulin et al. Time efficient scatter correction for time-of-flight PET. *Phys Med Biol*. 2019;64(7):075005

Artificial Neuron[1]



- **Nonlinear activation function** f
- **Multiple inputs, linearly combined**
- **Trainable weights** w_i **and bias** b
- **Supervised learning: adapt parameters to in-/output**

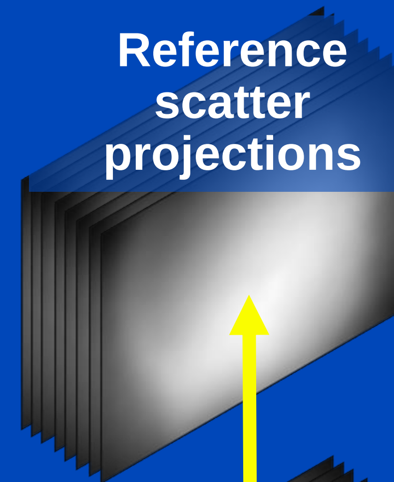
Convolutional Neural Networks

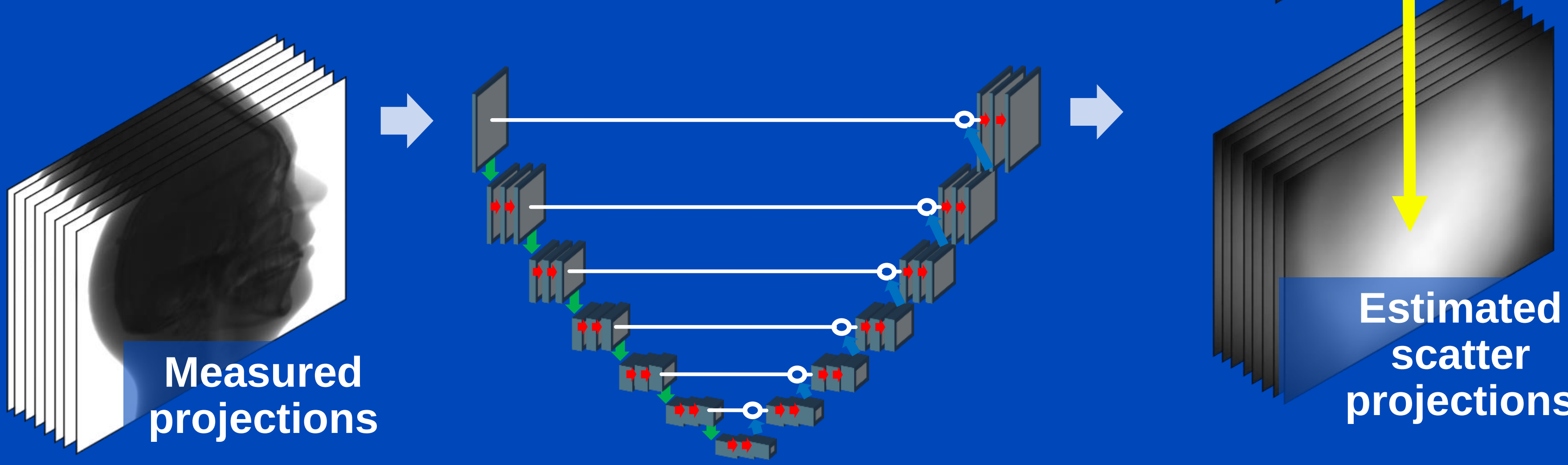


- **Fully-connected vs. convolutional layers of neurons**
- **Vector-valued inputs (images, channels, features)**

Deep Scatter Estimation in CT

- A 2-D CNN to **estimate scatter** from **scatter-contaminated** projections[1-3]
  - Trained using measurements and reference
  - Applied to individual projections
  - ➢ Real-time performance for cone-beam CT





[1] Maier, Berker, Sawall, Kachelrieß. *Proc SPIE*. 2018:105731L. [3] Maier, Kachelrieß et al. *Med Phys*. 2018;46(1):238-49.
[2] Maier, Kachelrieß et al. *J Nondestruct Eval*. 2018;37(3):57. Also compare Hansen et al. *Med Phys*. 2018;45(11):4916-26.

Previous Work in PET

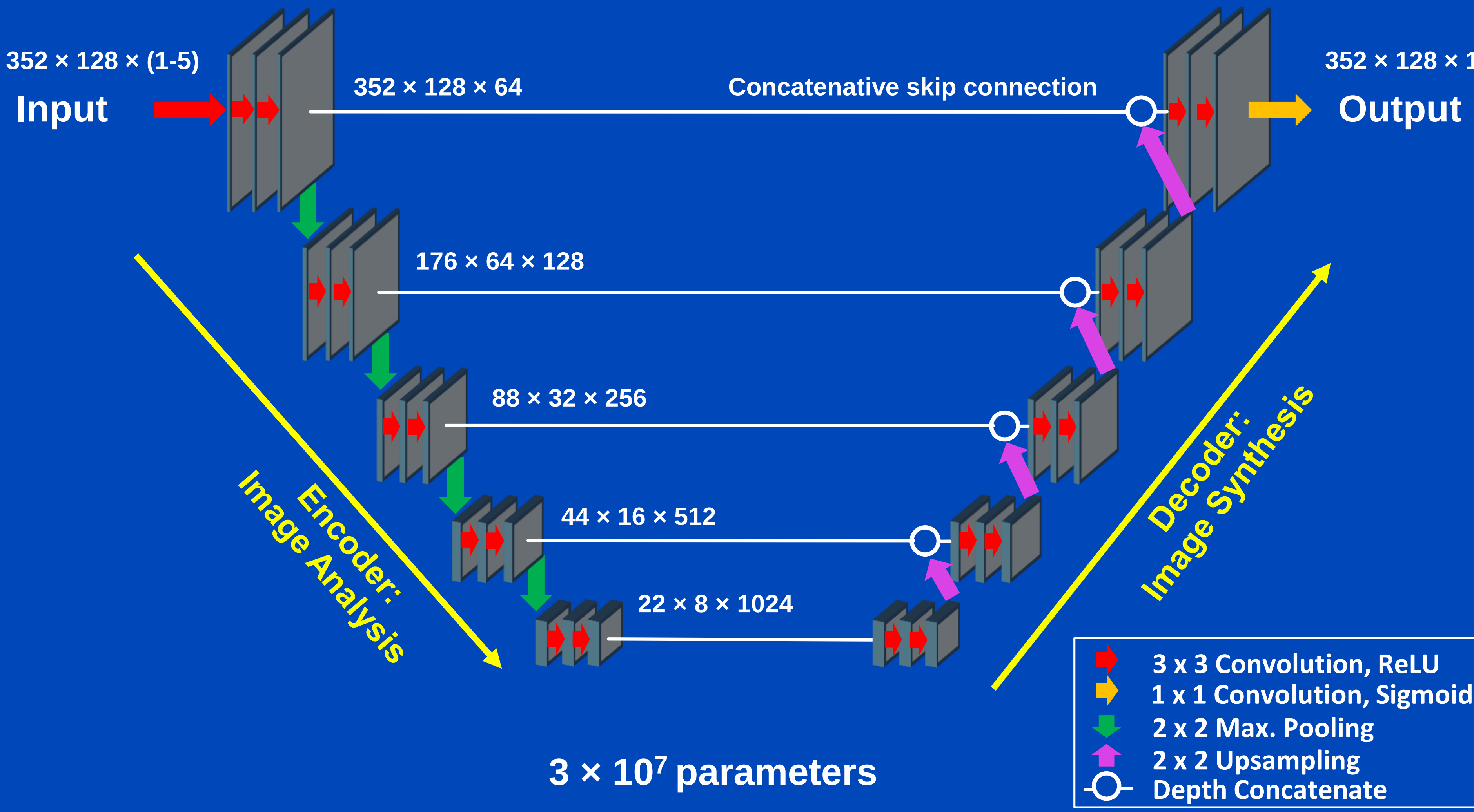
- Emission and attenuation, detector data[1]
  - 14 phantoms (13 training, 1 validation)
- Emission and attenuation, detector data[2]
  - 20 whole-body patients (57/14 bed positions)
  - 3.6% mean absolute error (+ one outlier)
- Emission only, reconstructed images[3]
  - 35 brain patients (25/10 scans)
  - 1% ± 5% deviation (+ one outlier)

[1] Qian, Rui, De Man. IEEE NSS/MIC 2017;M04-1. [2] Berker, Maier. Kachelrieß. IEEE NSS/MIC 2018;M-17-04.
[3] Yang, Park, Gullberg, Seo. Phys Med Biol. 2019;64(7):075019.

Aim

- Investigate the need to input
  emission and/or attenuation data
- Understand the influence of various other
  transformations of the input data

Network Structure: U-Net[1]



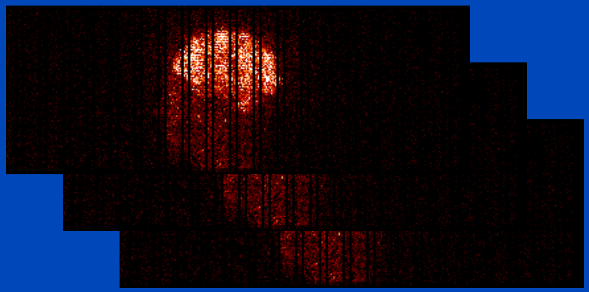
3×10^7 parameters

[1] Ronneberger O, Fischer P, Brox T. *MICCAI.* 2015:234-41.

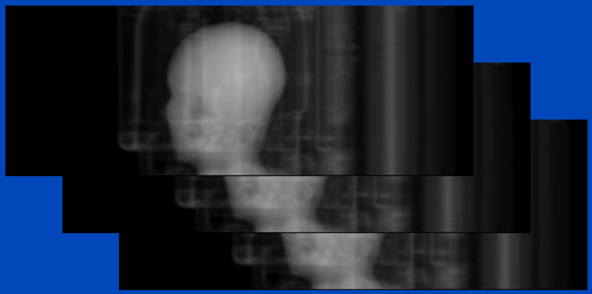
Available Patient Data

- **20 patients:** FDG, Siemens Biograph mMR

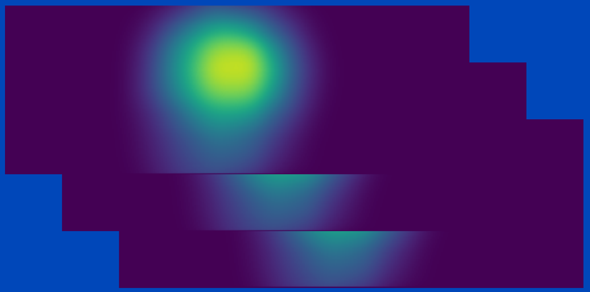
Prompts



ACFs



Scatter

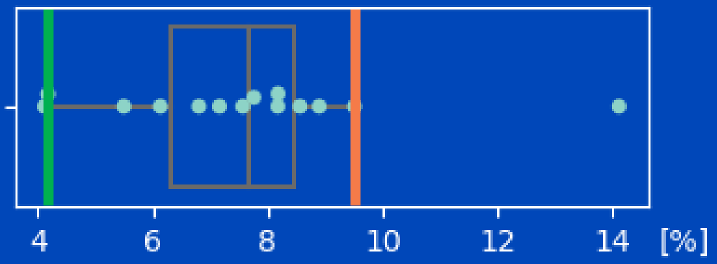


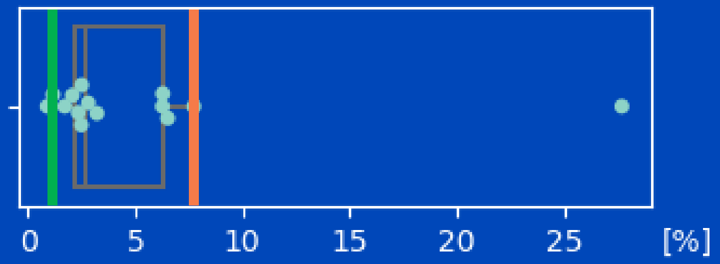
- **Padding:** 344 × 127 → 352 × 128 pixels

Results: Accuracy[1]

Normalized Mean Absolute Error: $\mathrm{NMAE} = \frac{\sum_i |DSE_i - SSS_i|}{\sum_i |SSS_i|}$

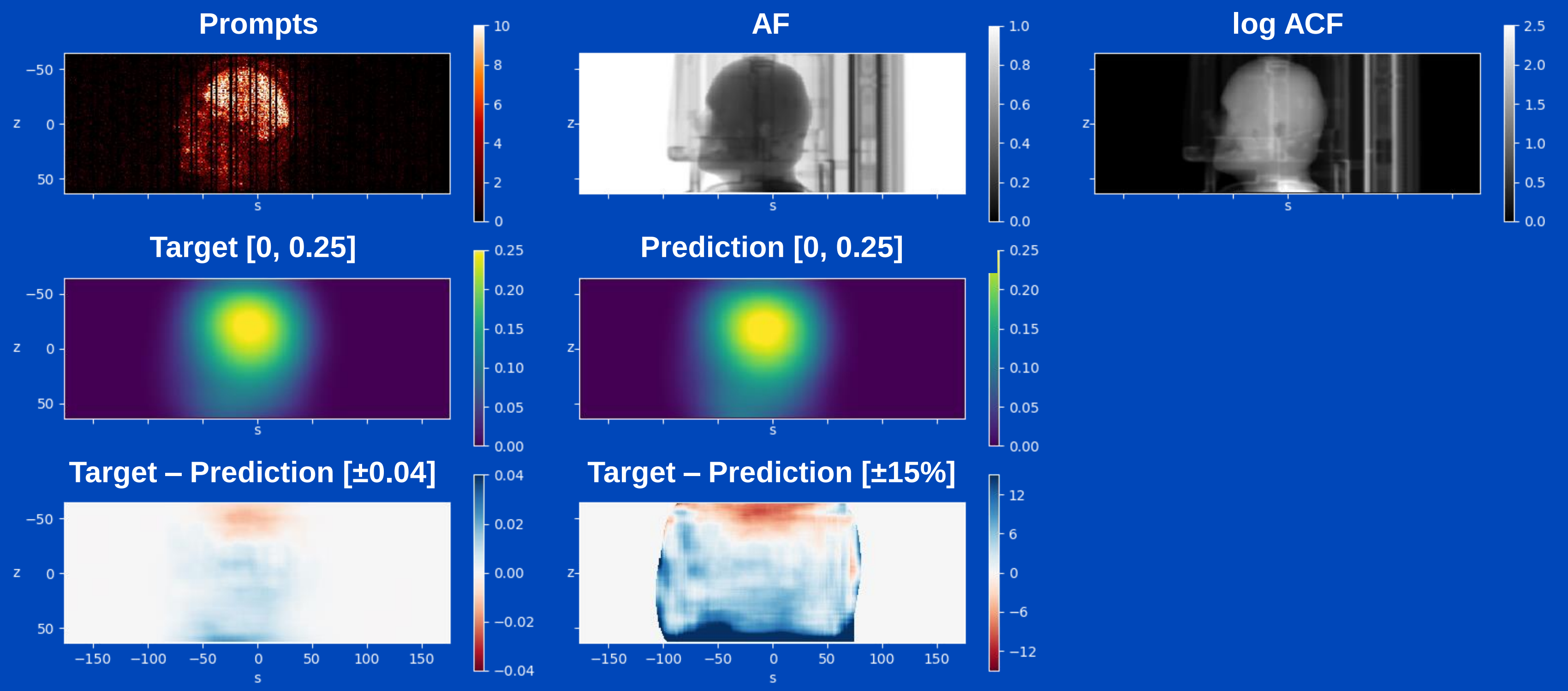
	Scatter projections	PET reconstructions
Mean/Std	7.1 ± 1.7 %	3.6 ± 2.2 %
Range	4 – 10 %	1 – 8 %
Outlier	14 %	28 %





[1] Berker, Maier. Kachelrieß. IEEE NSS/MIC 2018;M-17-04.
NMAE, normalized mean absolute error (per bed position)

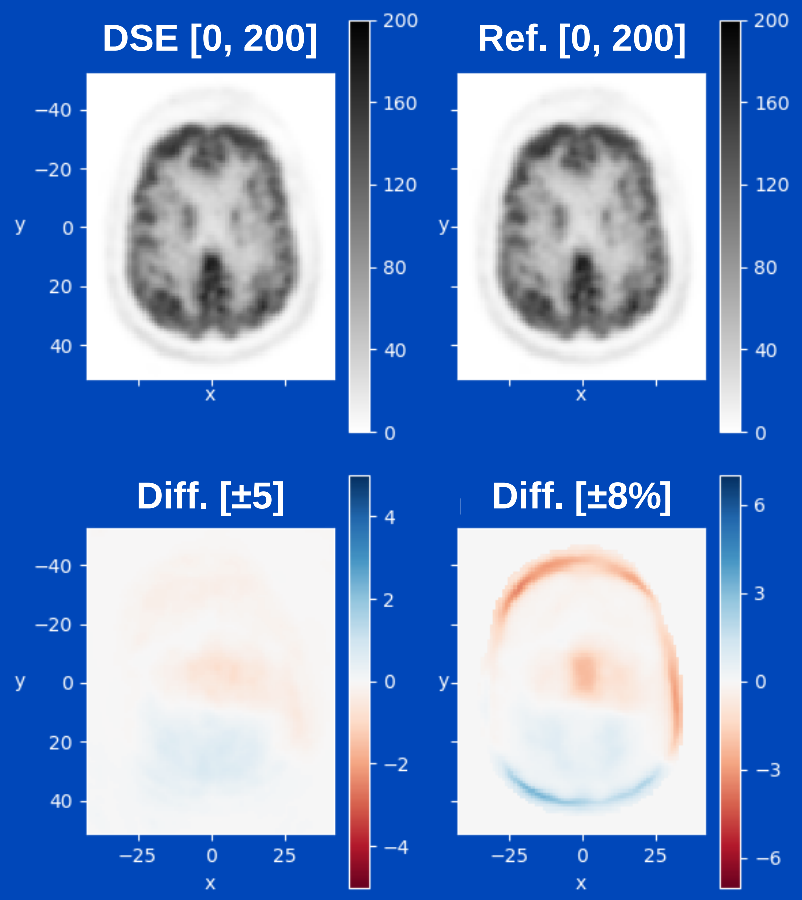
Results: Best Case



- **Best case:** **brain bed position**

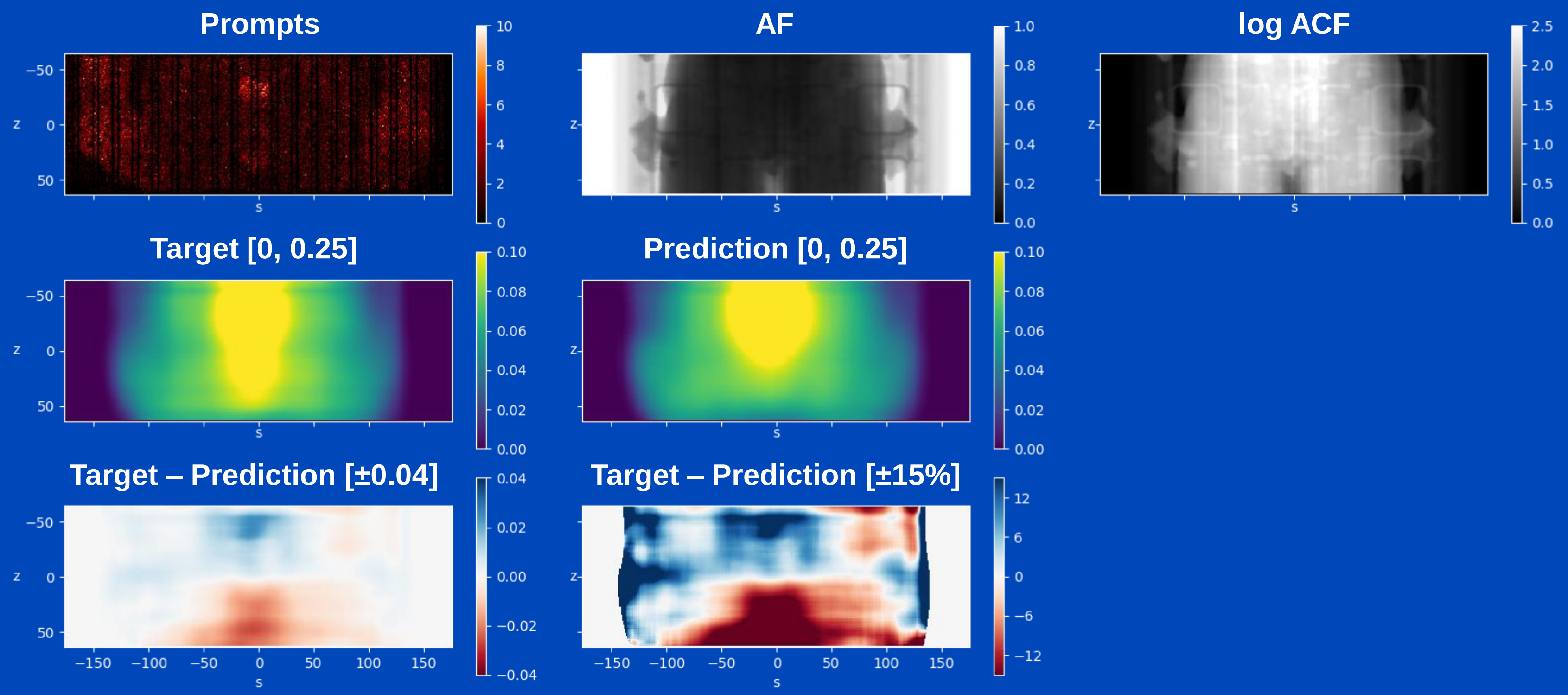
Bed position e7876f, NMAE: 4.17 % (scatter), 1.18 % (recon)
252 views, 25 fps. DSE filtered for display along views (Gaussian, FWHM 3.5 views)

Results: Best Case



Bed position e7876f, NMAE: 4.17 % (scatter), 1.18 % (recon)
Reconstruction, transaxial (a.u.), 10 fps

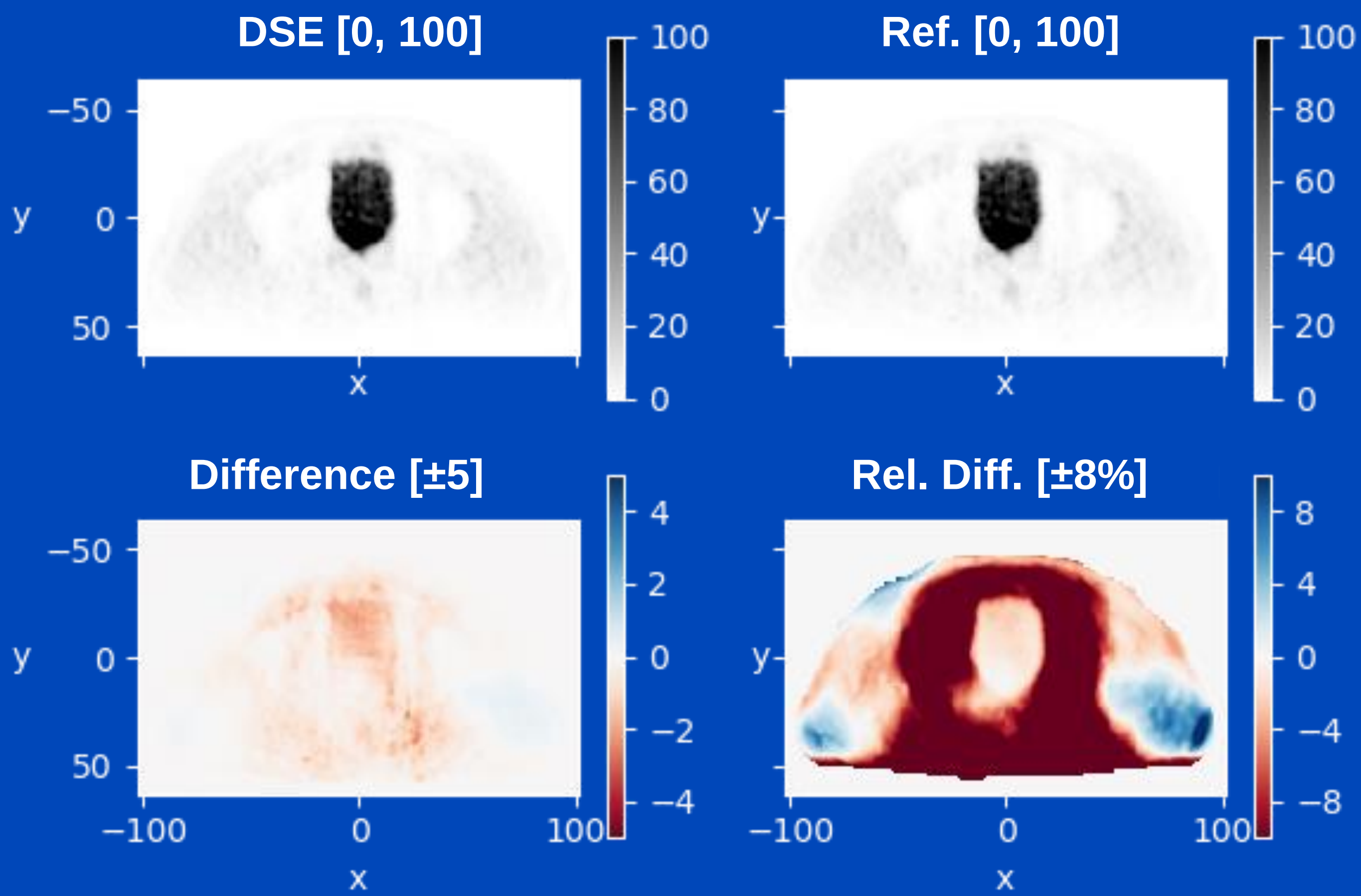
Results: Worst Case



- **Worst case: filled bladder inside the FOV**

Bed position fce8f8, NMAE: 8.89 % (scatter), 7.75 % (recon)
252 views, 25 fps. DSE filtered for display along views (Gaussian, FWHM 3.5 views)

Results: Worst Case



Original vs. Current Parameters

- Network
  - Dropout
  - Sigmoid output
  - Poisson loss function
- Implementation
  - TensorFlow-Keras v1.8-v1.12
  - 10 epochs

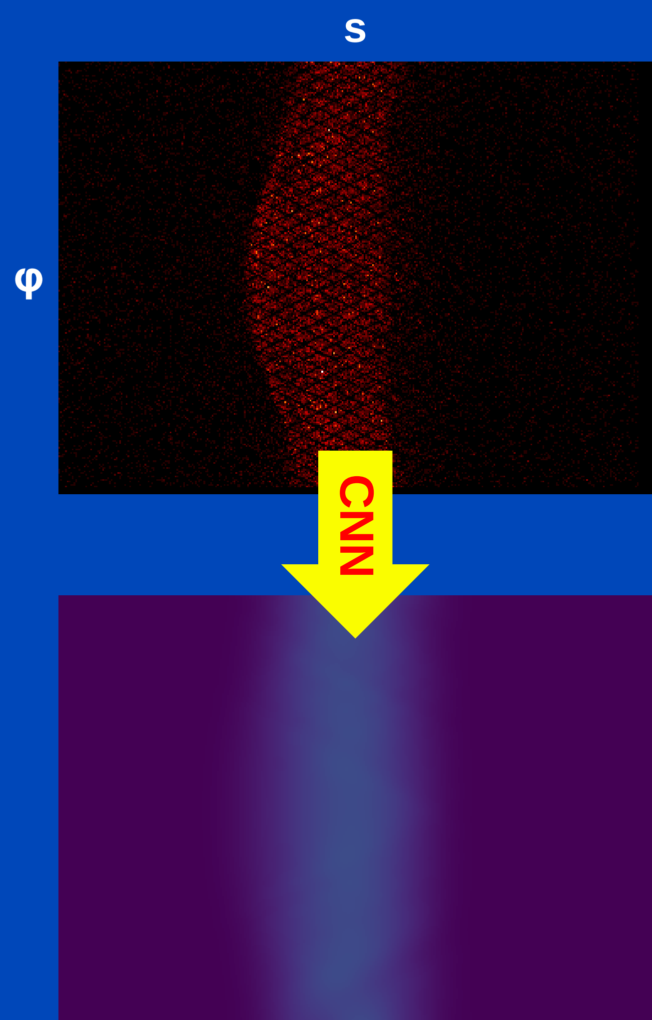
- Network
  - No dropout
  - ReLU output
  - Mean absolute error
- Implementation
  - TensorFlow-Keras v1.13.1
  - 5 epochs

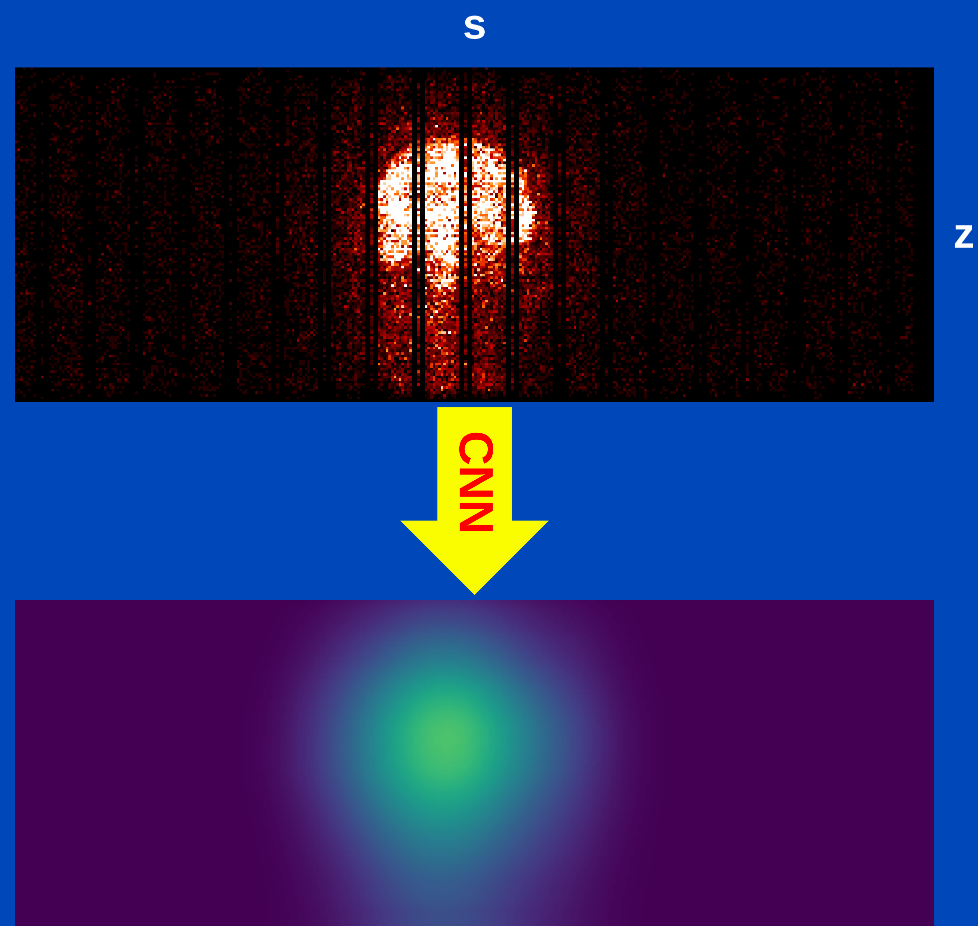
- Adam optimizer
  - Batch size 4, initial learning rate 10^{-4}
- Workstation
  - Intel Xeon E5-2667 v4 (2 x 8 cores, 256 GB), NVIDIA Quadro M5000 (2048 cores, 8 GB)

Specific Investigations

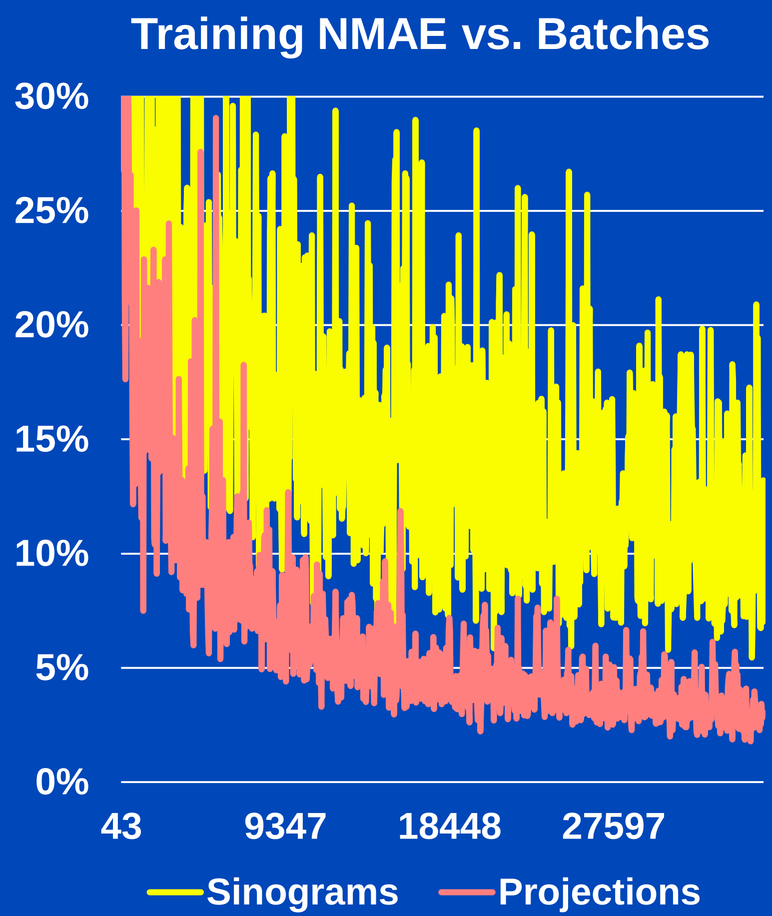
- Sinograms vs. projections
- Choice of input features
  - Emission *and/or* attenuation
  - Redundant combinations
- Number of samples
  - Data augmentation
  - Number of bed positions
- Transformations
  - Gap filling of prompts
  - Normalization of inputs
- Scatter scaling

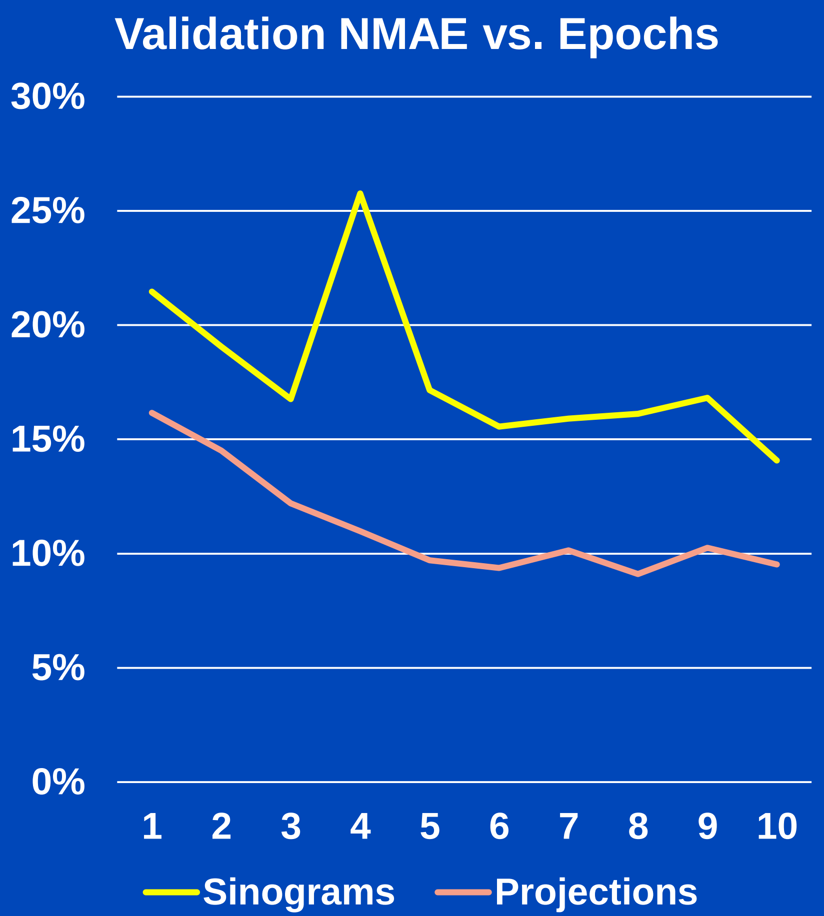
Sinograms vs. Projections





Projections vs. Sinograms





NMAE, normalized mean absolute error

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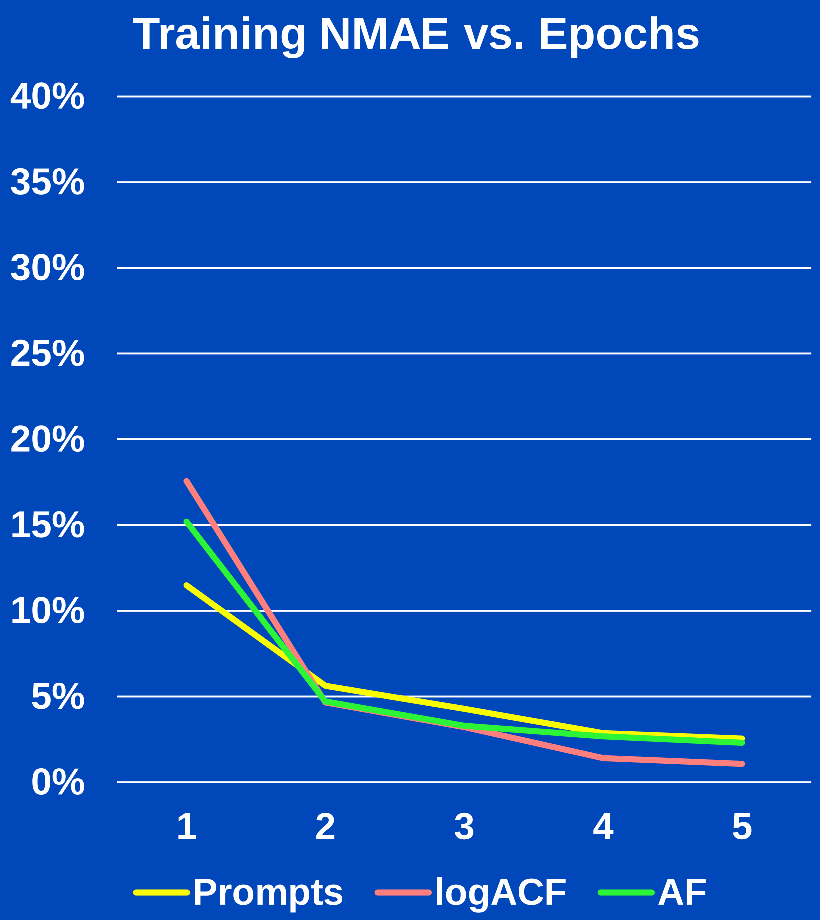
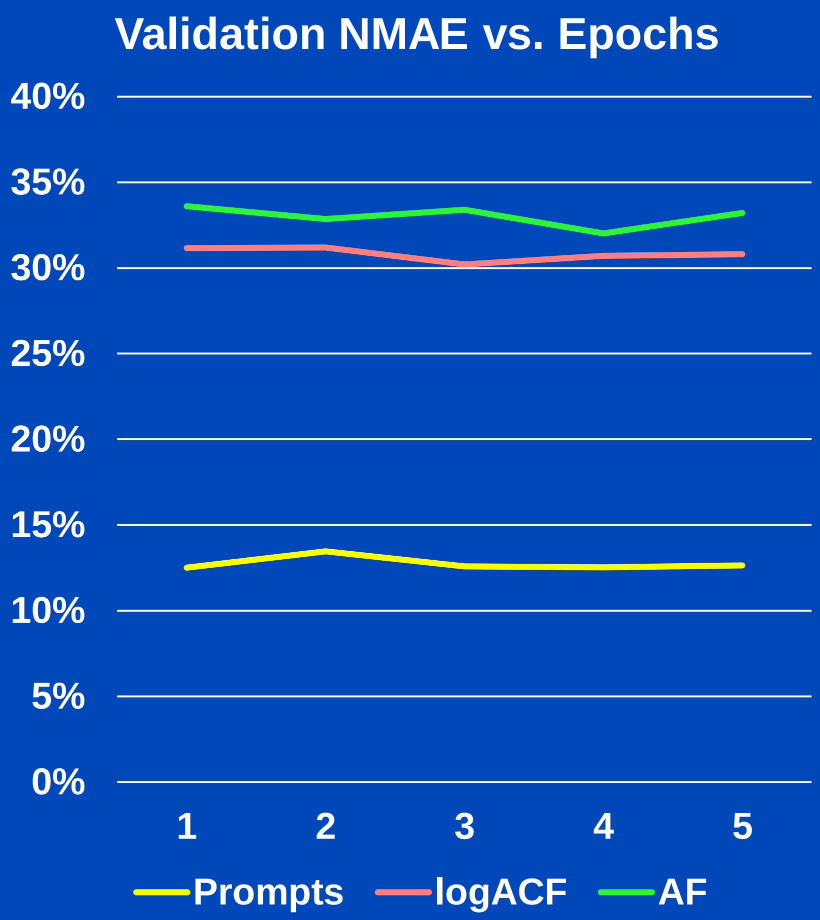
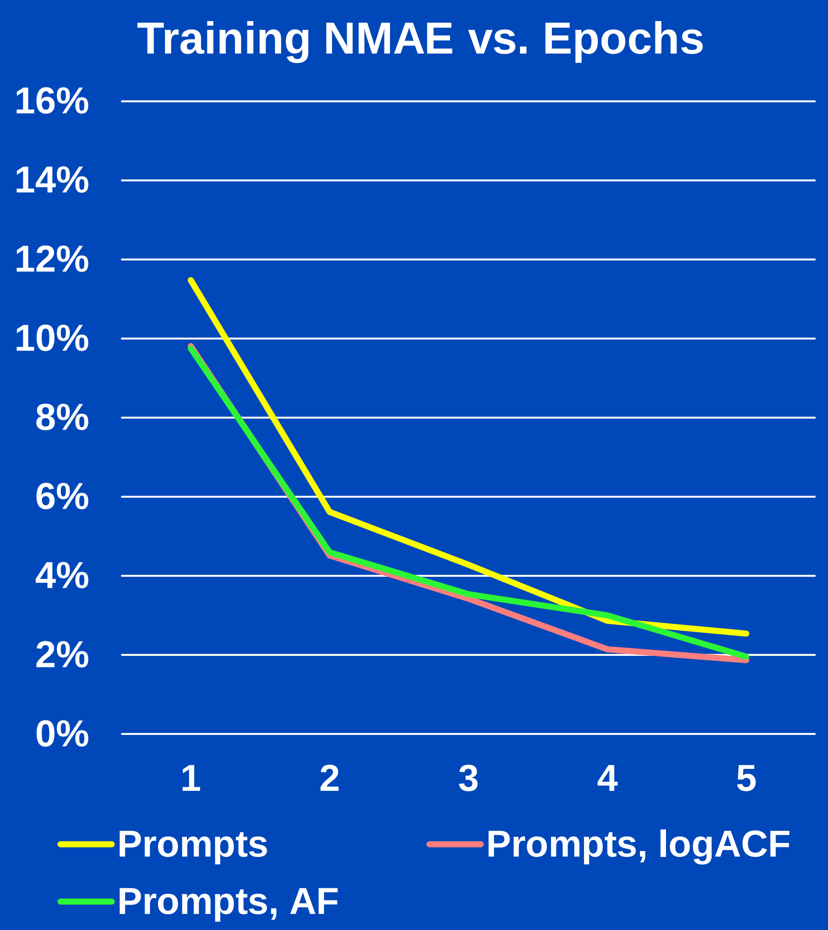
Emission *vs.* Attenuation

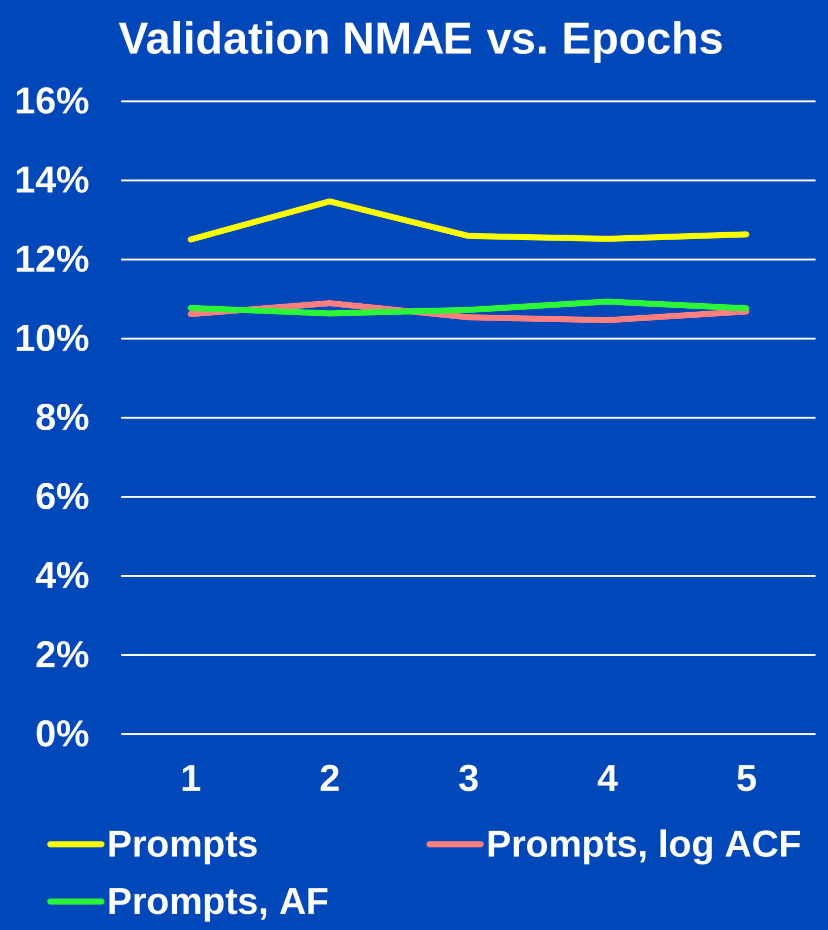




NMAE, normalized mean absolute error; ACF, attenuation correction factor; AF, attenuation factor

Emission *and* Attenuation

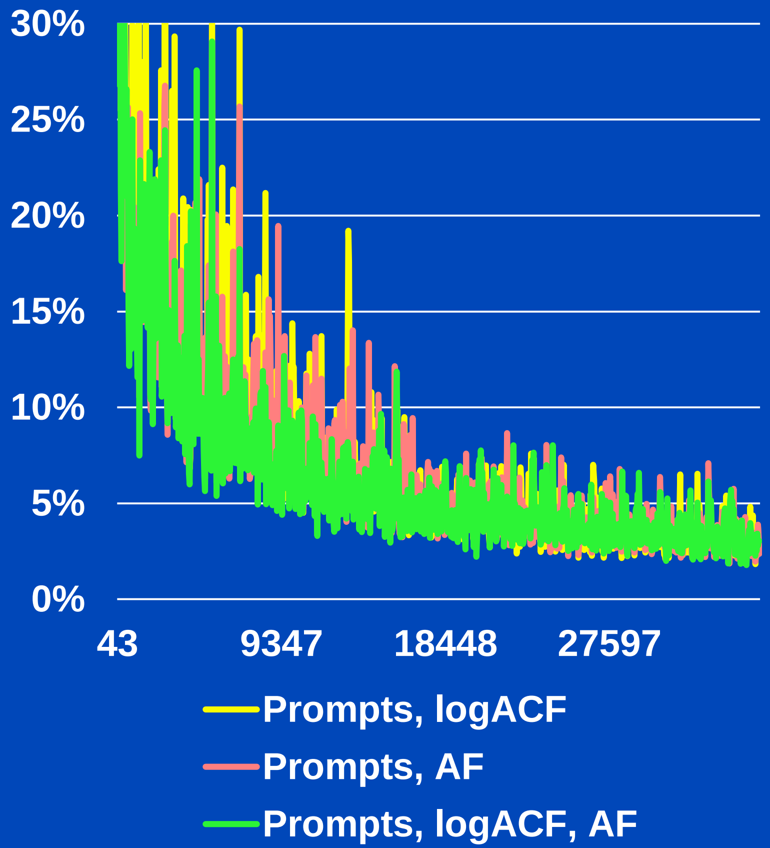




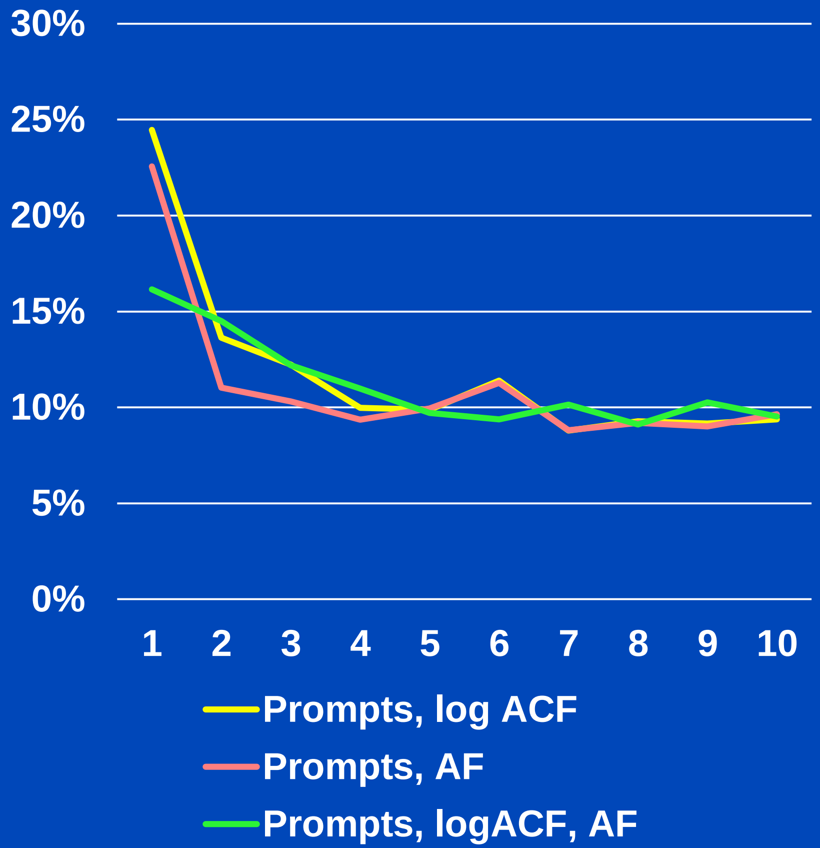
NMAE, normalized mean absolute error; ACF, attenuation correction factor; AF, attenuation factor

Redundant Features

Training NMAE vs. Epochs



Validation NMAE vs. Epochs



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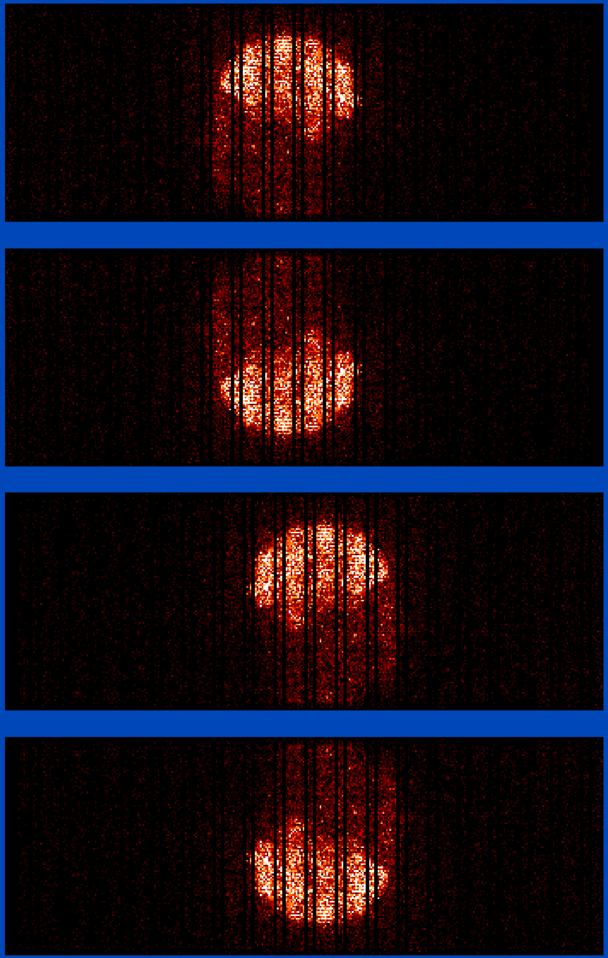
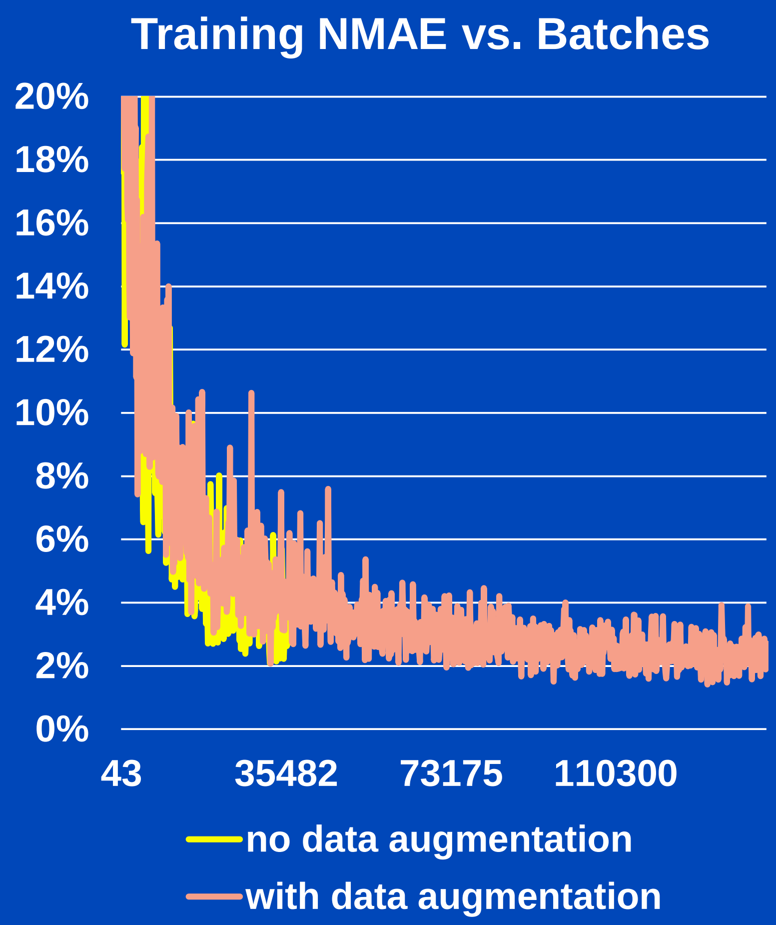
Data Augmentation

- 4 x number of samples
  - Vertical flipping
  - Horizontal flipping

- Expectation
  - Better generalization

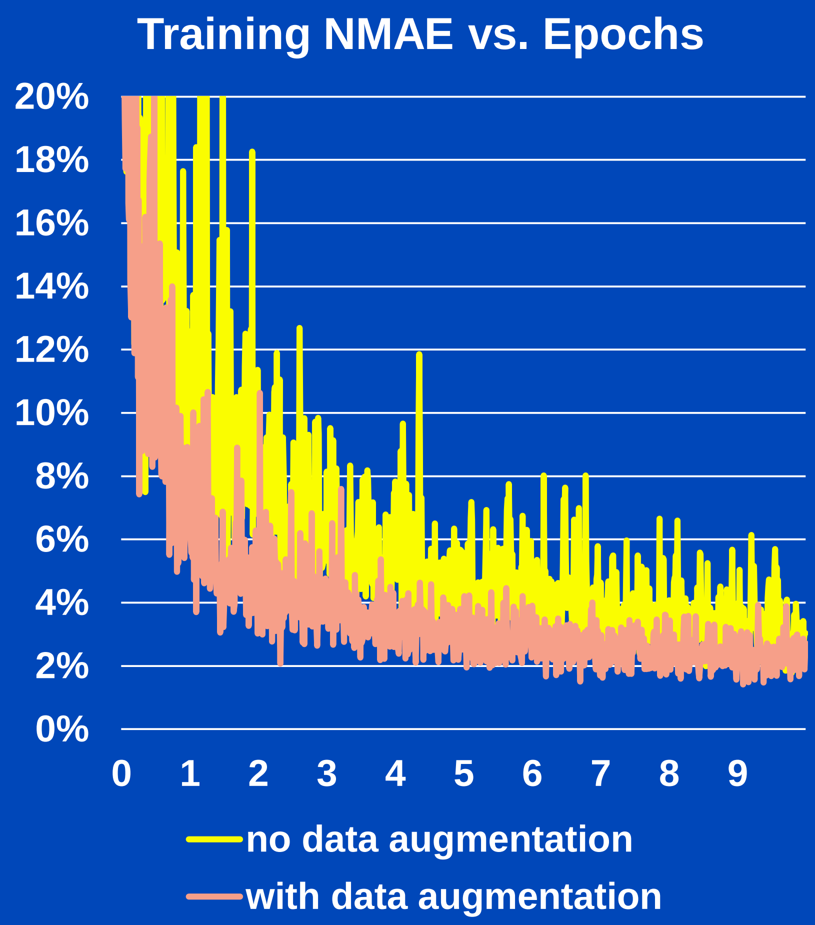


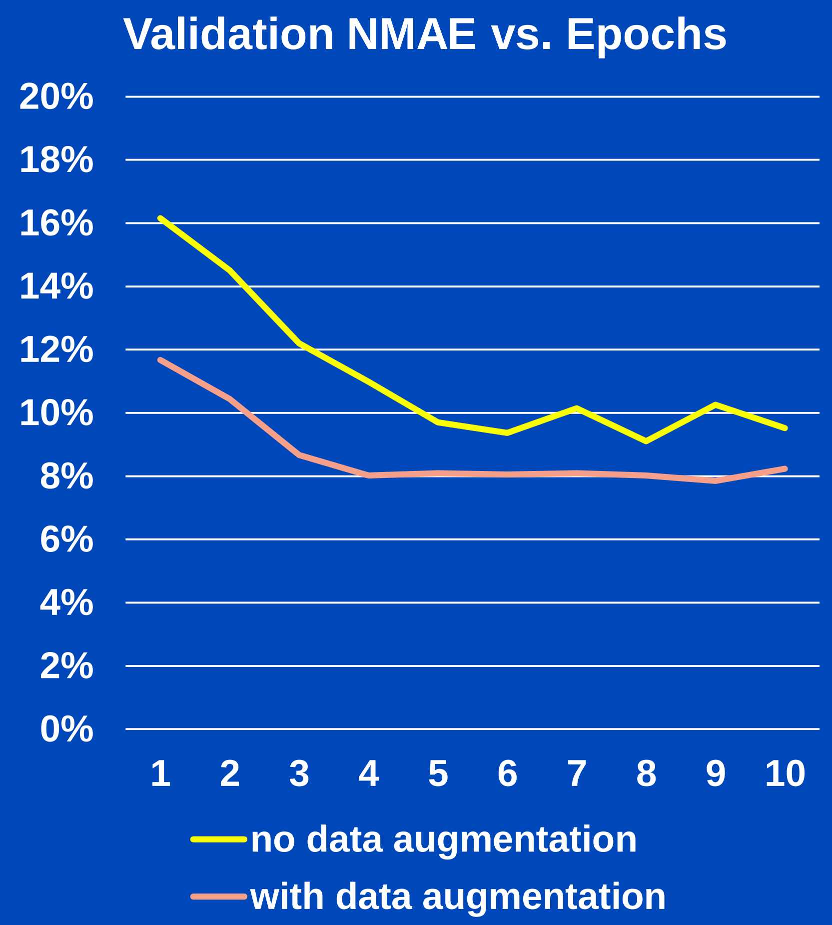
Data Augmentation



NMAE, normalized mean absolute error

Data Augmentation





NMAE, normalized mean absolute error

Number of Bed Positions

Previous study[1]

- 2-6 per patient (brain/lungs/pelvis)
- 57/14 bed positions
- 0.8% training NMAE
- 8.3% validation NMAE

Current study

- 5-7 per patient (brain to thighs)
- 88/18 bed positions
- 1.5% training NMAE
- 11.7% validation NMAE

[1] Berker, Maier. Kachelrieß. IEEE NSS/MIC 2018;M-17-04.
NMAE, normalized mean absolute error

Specific Investigations

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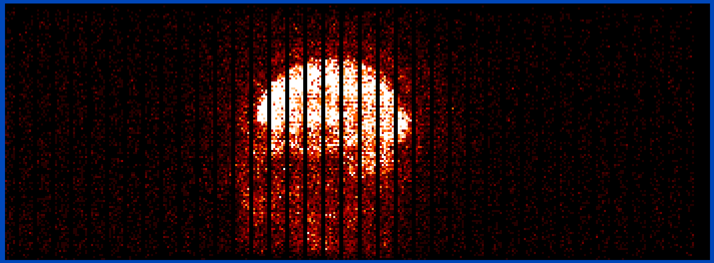
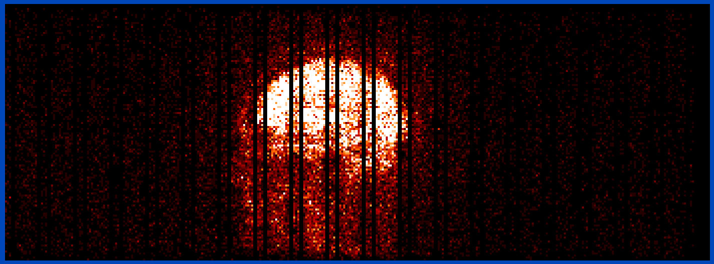
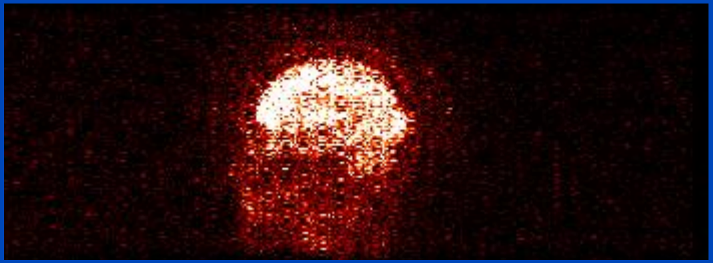
Gap Filling of Prompts

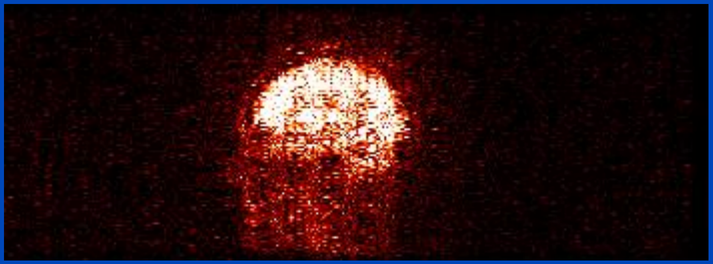
no gap filling



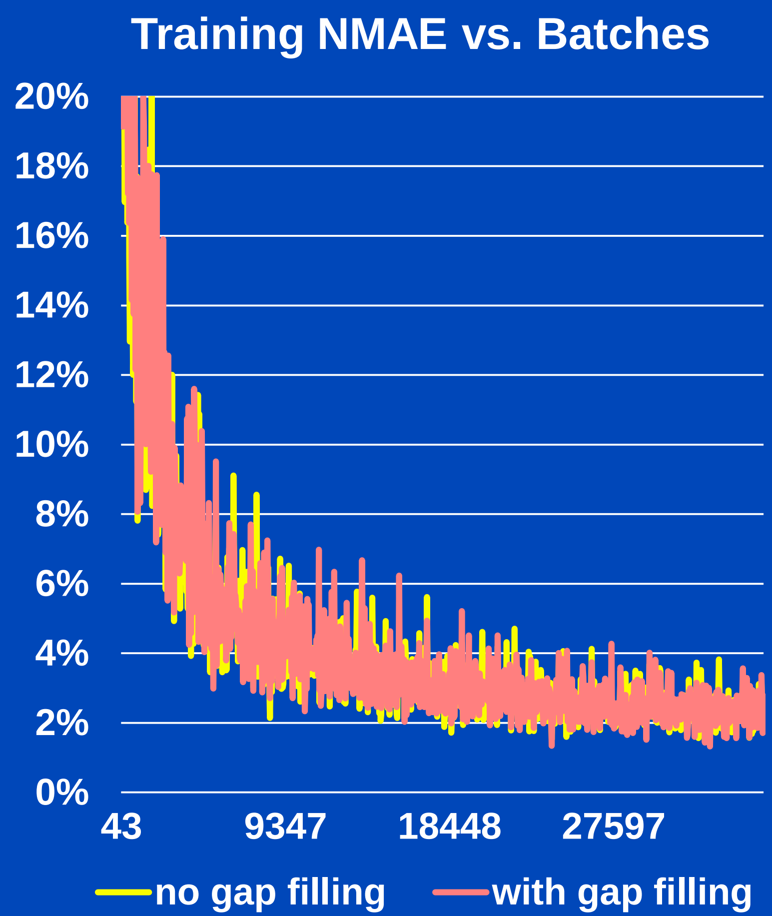


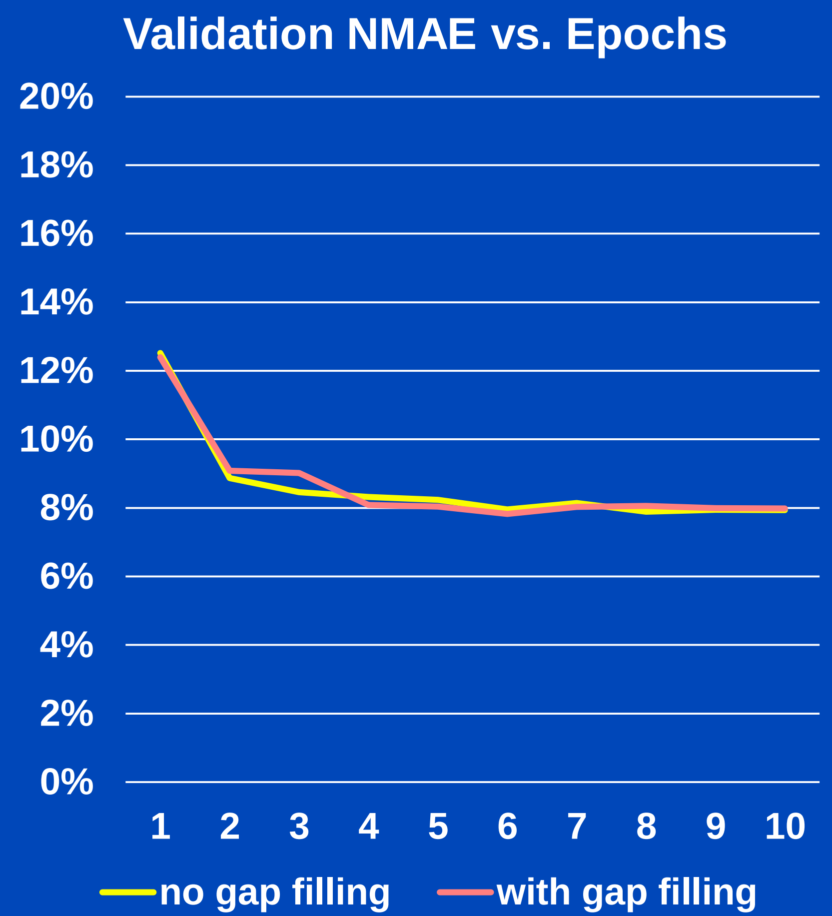
with gap filling





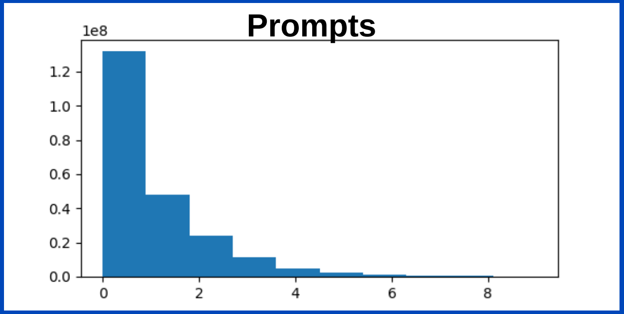
Gap Filling of Prompts

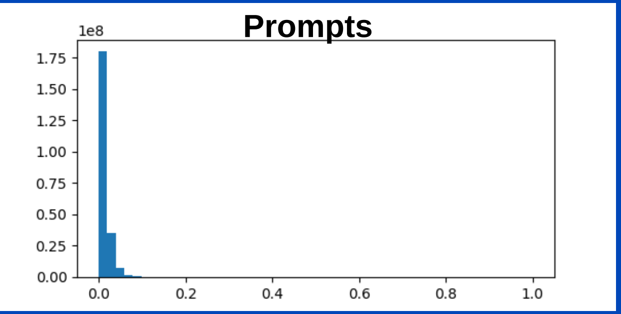


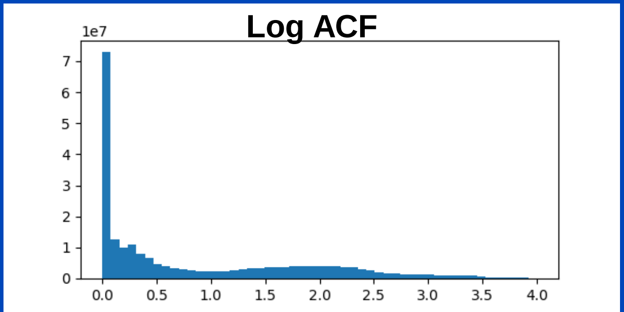


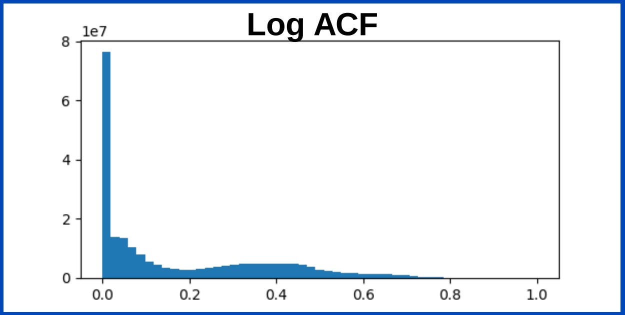
NMAE, normalized mean absolute error

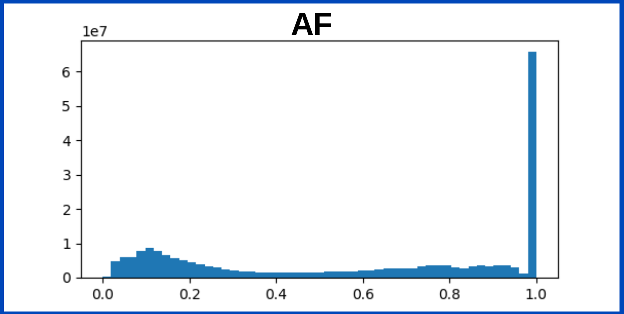
Input Normalization: Range [0, 1]

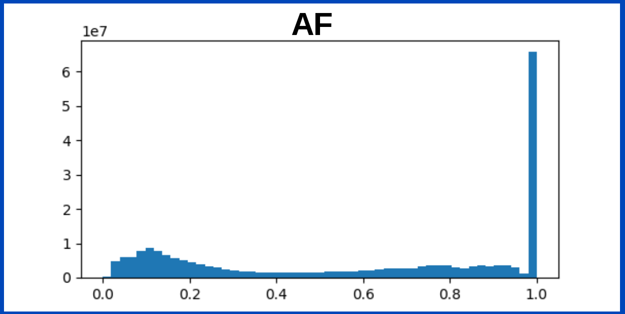






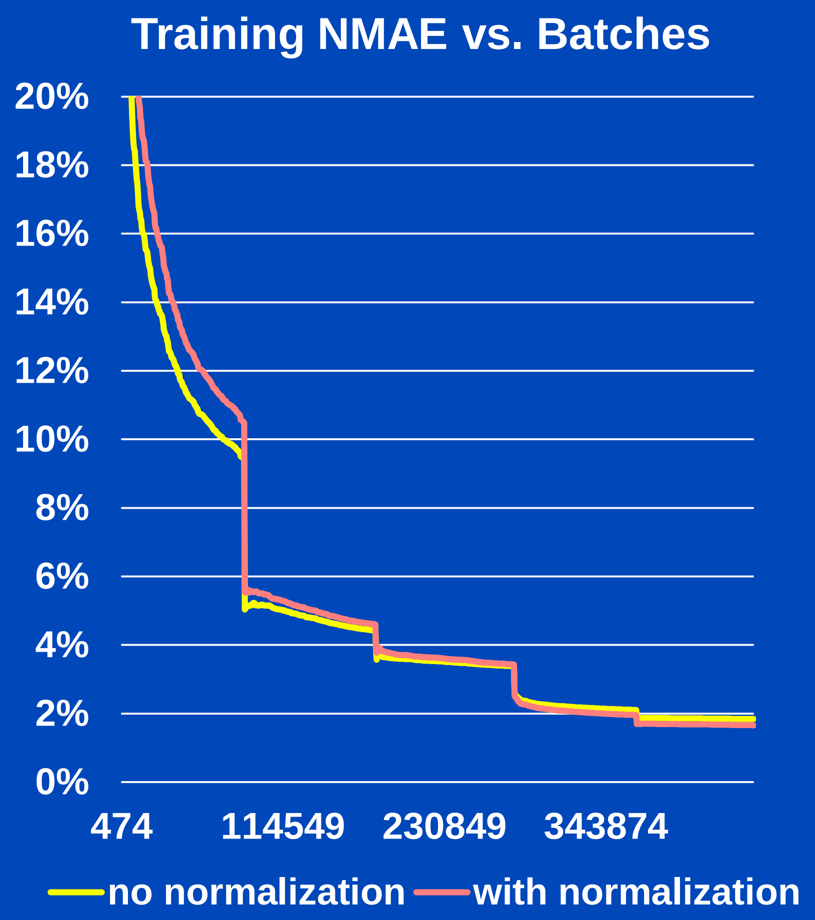


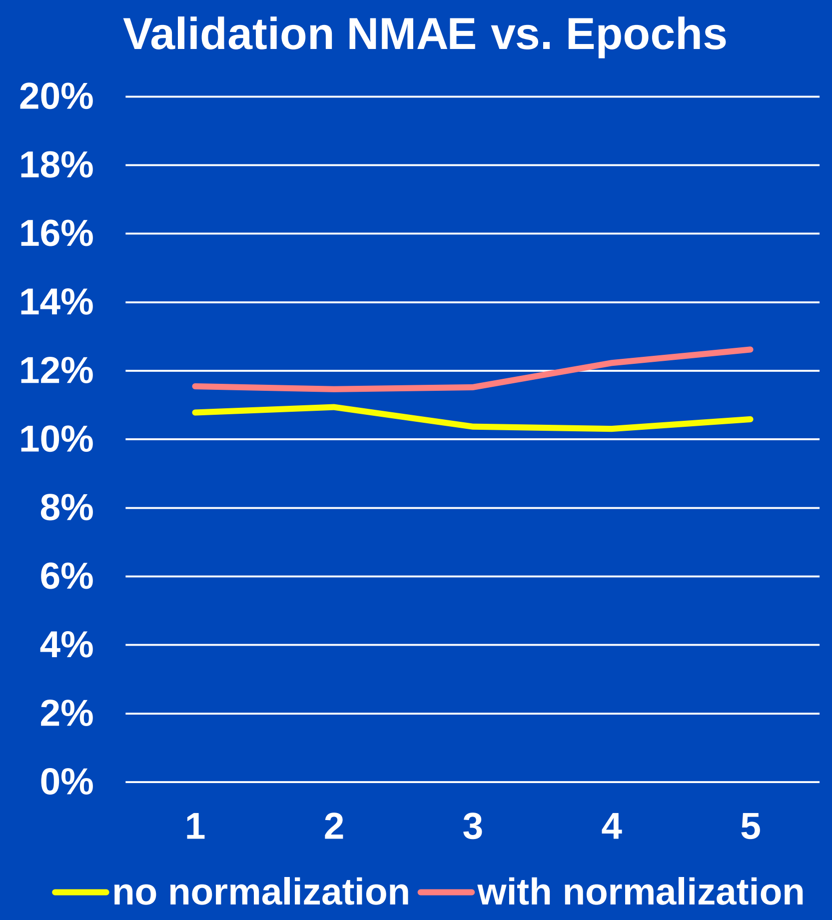




ACF, attenuation correction factor; AF, attenuation factor

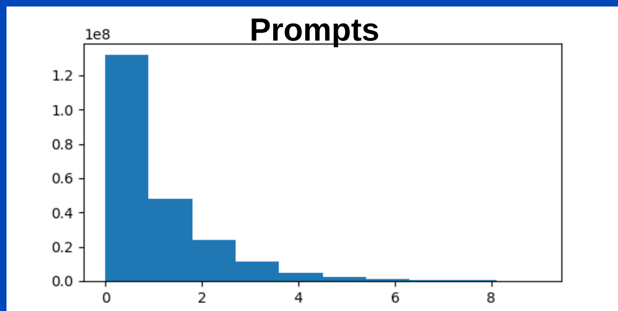
Input Normalization: [0, 1]

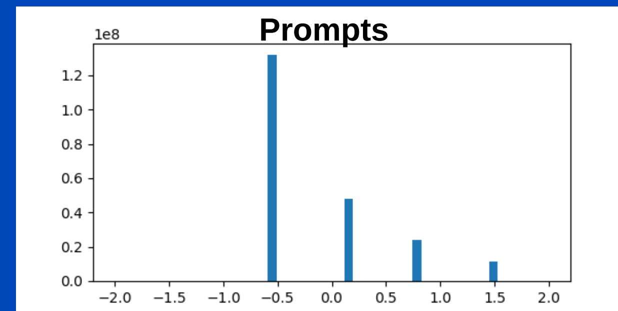


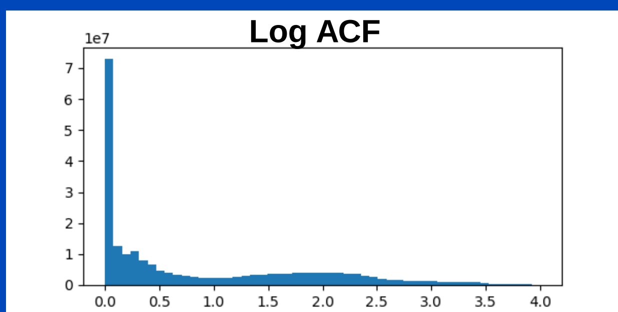


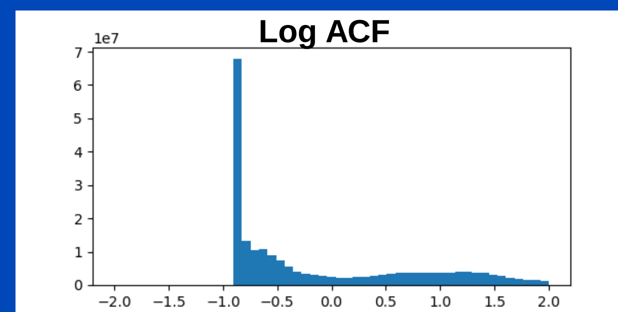
NMAE, normalized mean absolute error

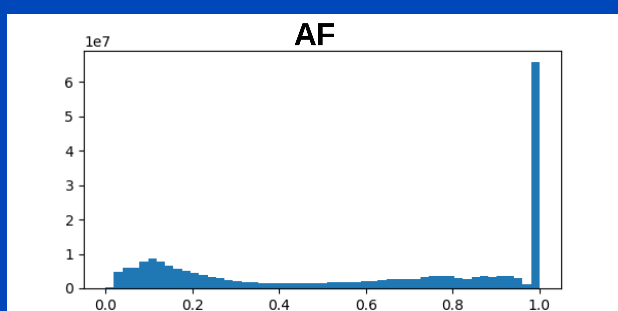
Input Normalization: Zero Mean, Unit Variance

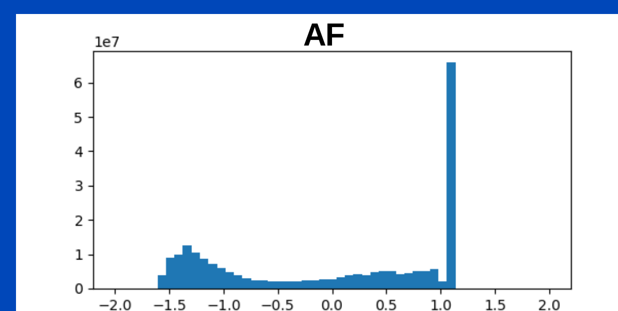






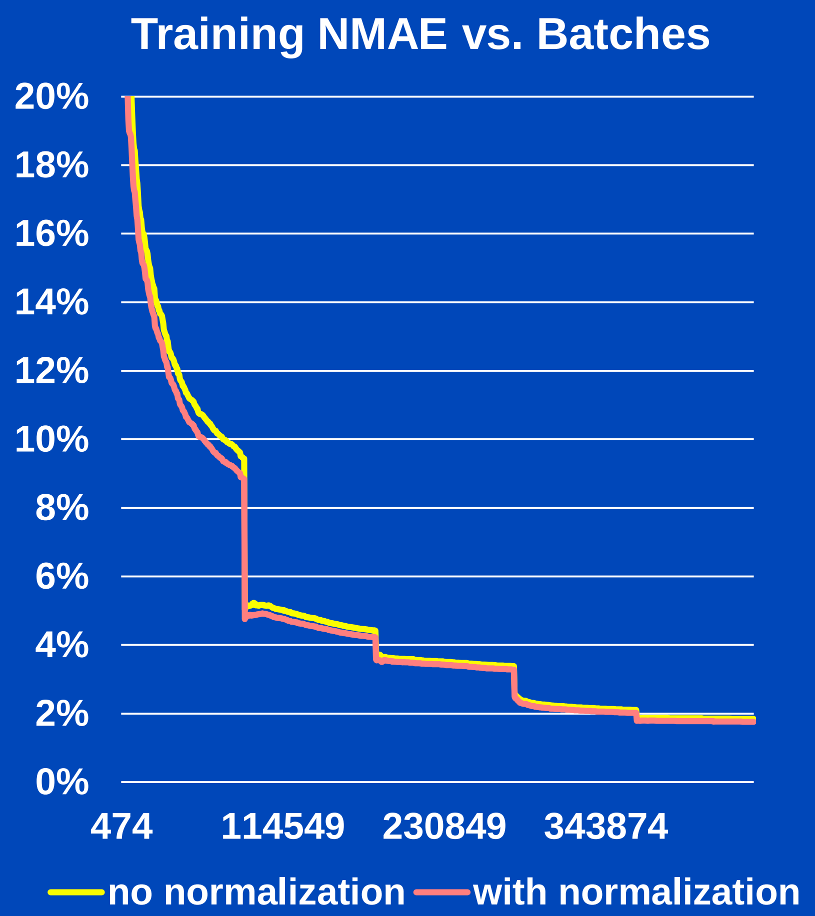


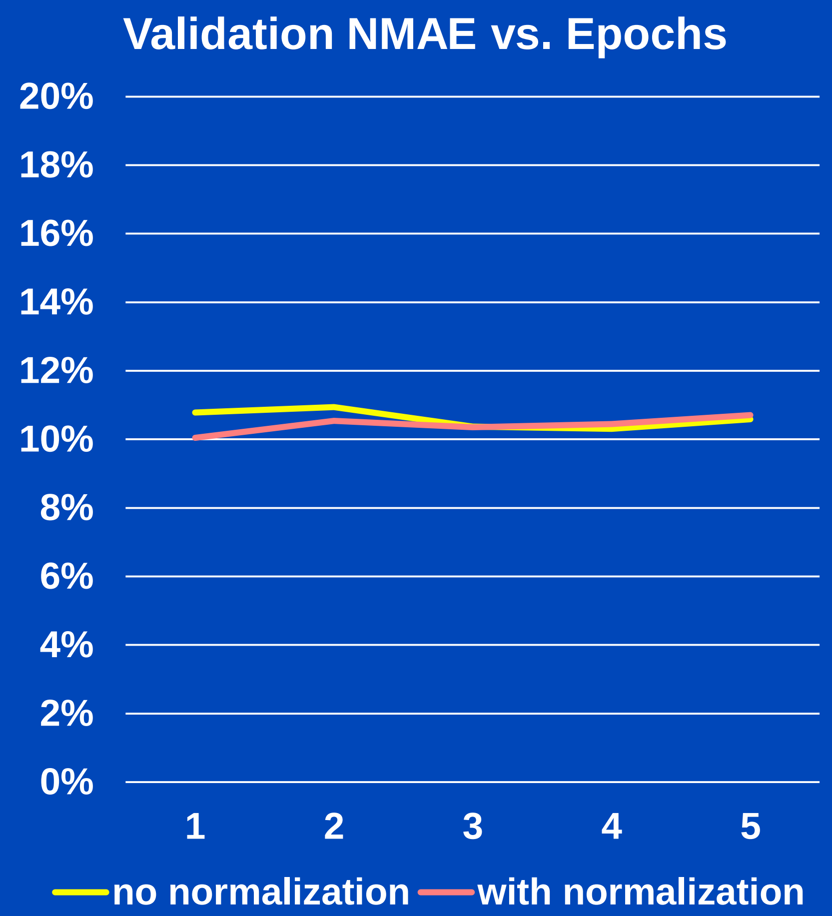




ACF, attenuation correction factor; AF, attenuation factor

Input Normalization: Zero Mean, Unit Variance



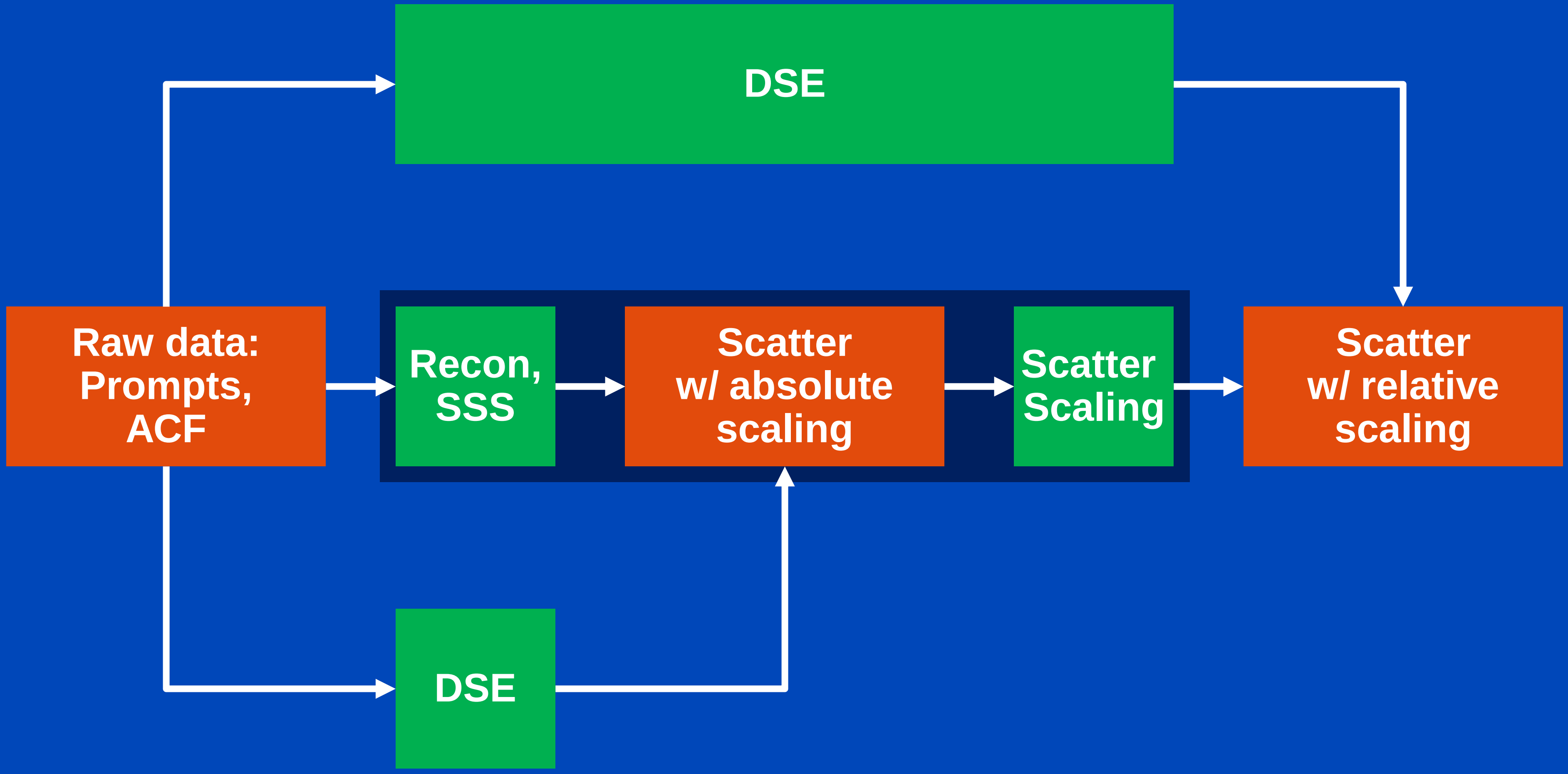


NMAE, normalized mean absolute error

Specific Investigations

- **Sinograms vs. projections**
- **Choice of input features**
  - **Emission *and/or* attenuation**
  - **Redundant combinations**
- **Number of samples**
  - **Data augmentation**
  - **Number of bed positions**
- **Transformations**
  - **Gap filling of prompts**
  - **Normalization of inputs**
- **Scatter scaling**

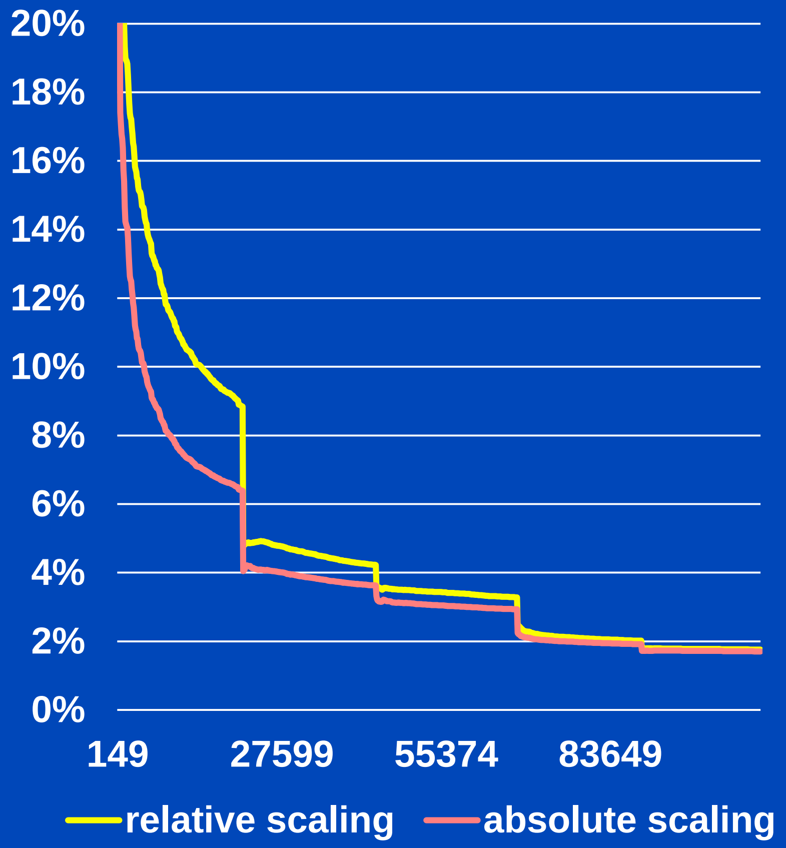
Scatter Scaling



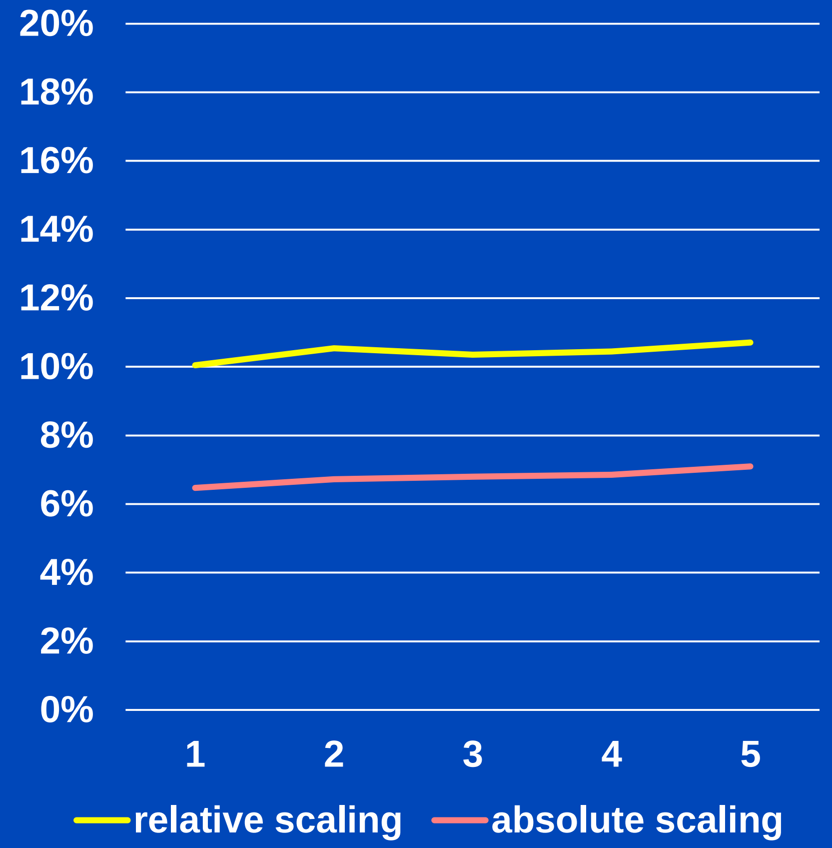
SSS, single scatter simulation; DSE, deep scatter estimation

Scatter Scaling

Training NMAE vs. Batches

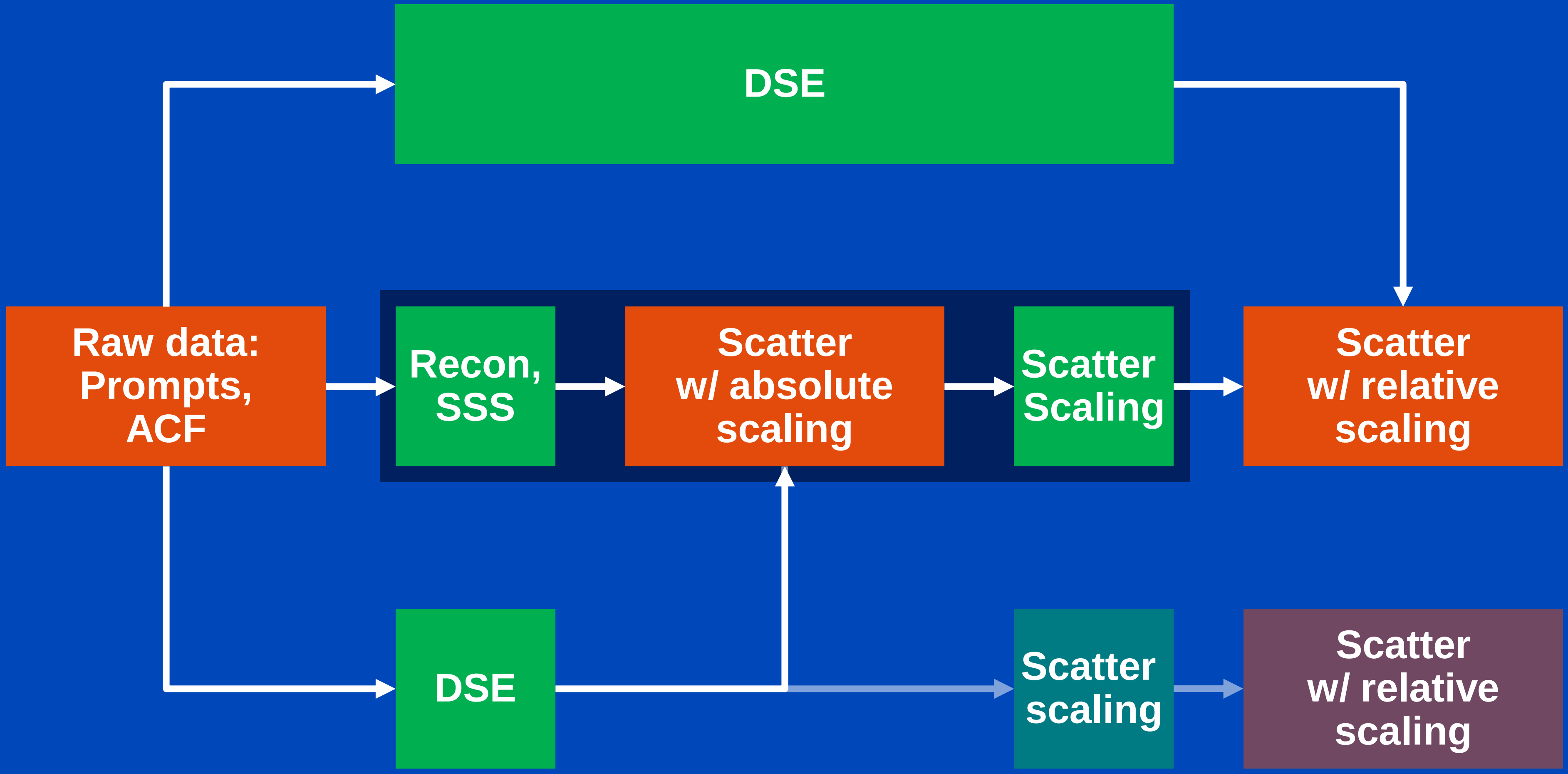


Validation NMAE vs. Epochs



NMAE, normalized mean absolute error

Scatter Scaling



SSS, single scatter simulation; DSE, deep scatter estimation

Conclusion

- A U-Net CNN can reproduce Siemens SSS with <7% NMAE
- No improvements seen by
  - additional bed positions (less specialized CNN, +3% NMAE)
  - redundant features (only for smaller dataset)
  - gap filling, input normalization
- Improvements seen by
  - using projections rather than sinograms (~5% NMAE)
  - data augmentation (~2% NMAE)
  - using emission *and* attenuation data (~2% NMAE)
  - training without scatter scaling (~4% NMAE)
- Aim: Deep Scatter Estimation trained with Monte Carlo scatter

SSS, single scatter simulation

Thank You!

This presentation will soon be available at www.dkfz.de/ct.

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