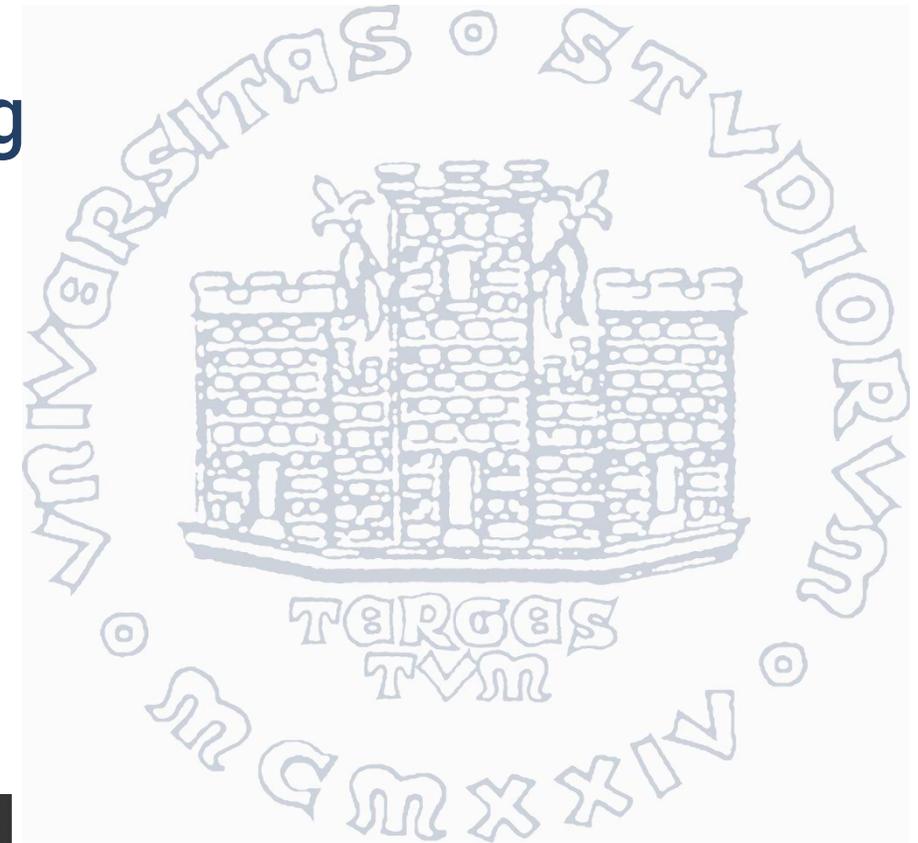


Simulations & ML in medical imaging

Stevan Vrbaski



Duke Radiology



Elettra Sincrotrone Trieste



- Virtual simulations performed and presented here are part of DukeSim virtual platform developed at CVIT, Duke University, USA
- Other similar software are Victre, XCIST, ...
- Experimental part was performed in Trieste, Italy



PART I – computer simulations in medical imaging

- Virtual imaging simulations: how and why to virtual imaging?
- Simulation parts: virtual humans and virtual detectors
- Spectral CT: modeling photon-counting detectors

PART II – machine learning in medical imaging

- Beyond traditional radiology: density and effective atomic number



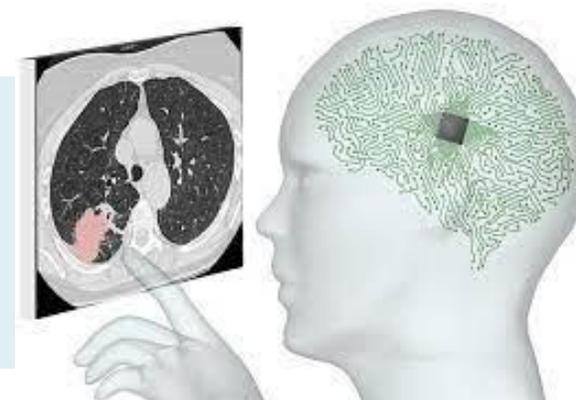
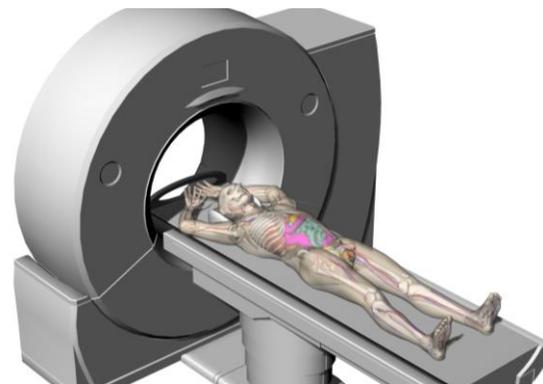
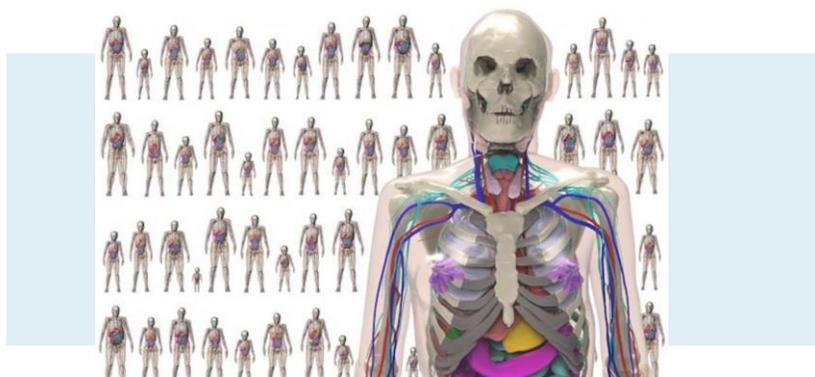
How to virtual imaging?



Real world



Virtual world





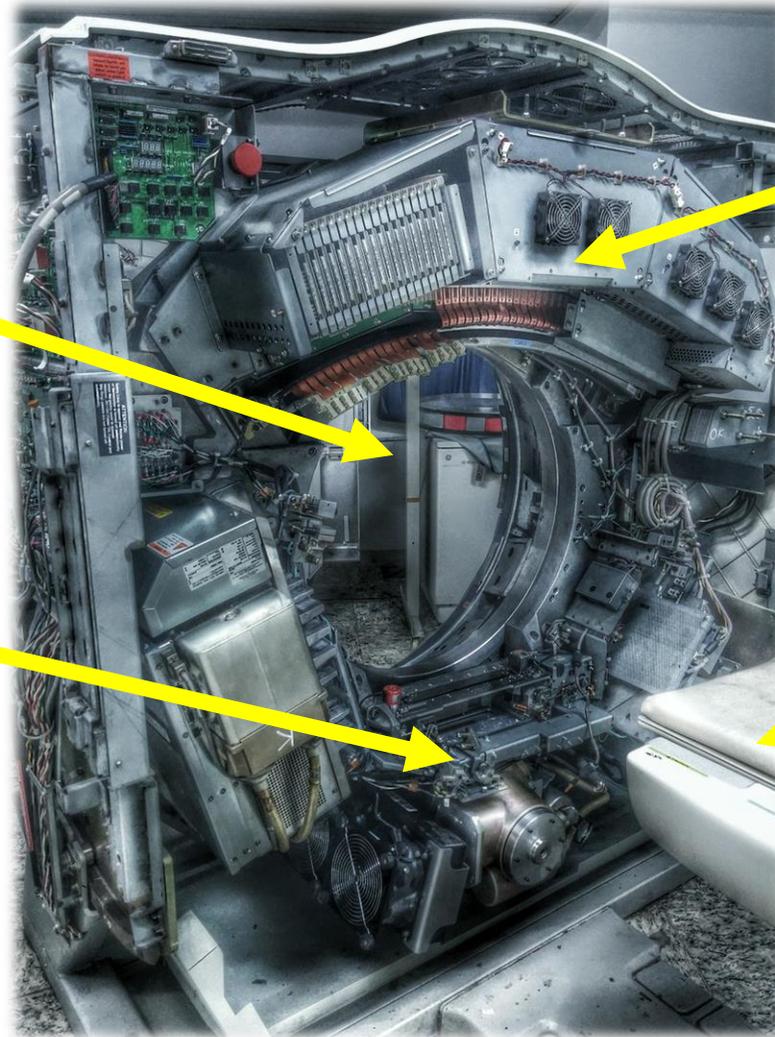
Why to virtual imaging?



Technology development

Geometry?
Magnification?

Source type?
What power?
Size of focal spot?



Which detector?
Detector size?
Pixel size?

Couch material?



Why to virtual imaging?



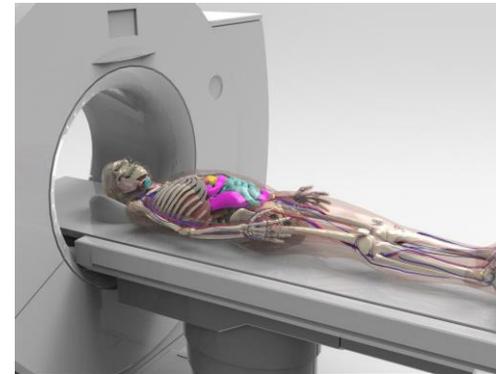
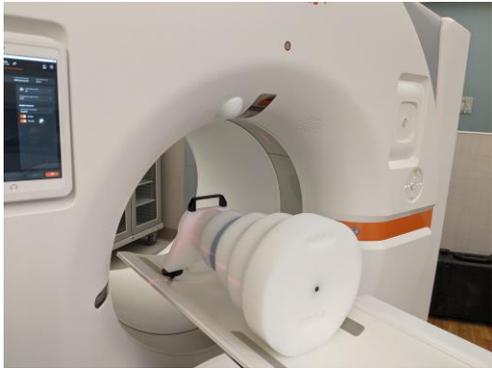
Technology evaluation – virtual imaging trials

physical phantoms

virtual

clinical

credibility



not anthropomorphic
not disease specific
not diverse
simple

ground truth limited
expensive
dose concern
complex

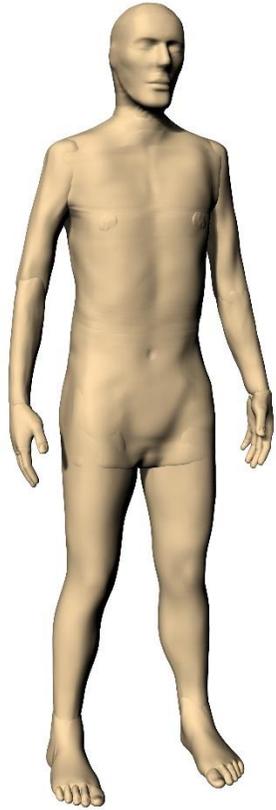


Anthropomorphic phantoms: virtual humans



UNIVERSITÀ
DEGLI STUDI DI TRIESTE

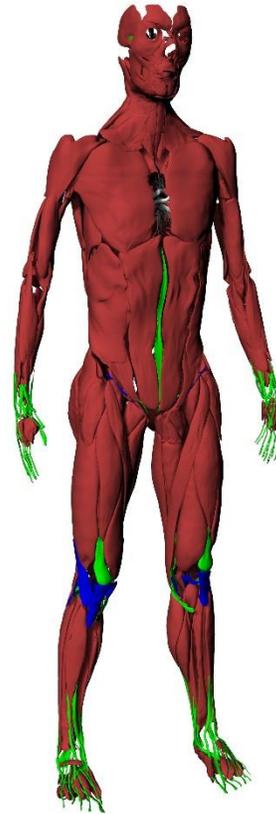
body surface



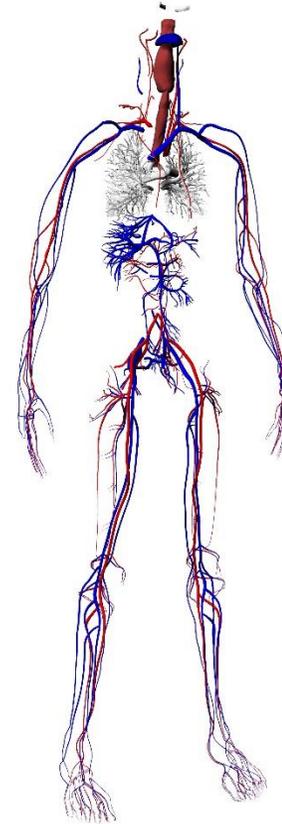
organs



muscles



vasculature

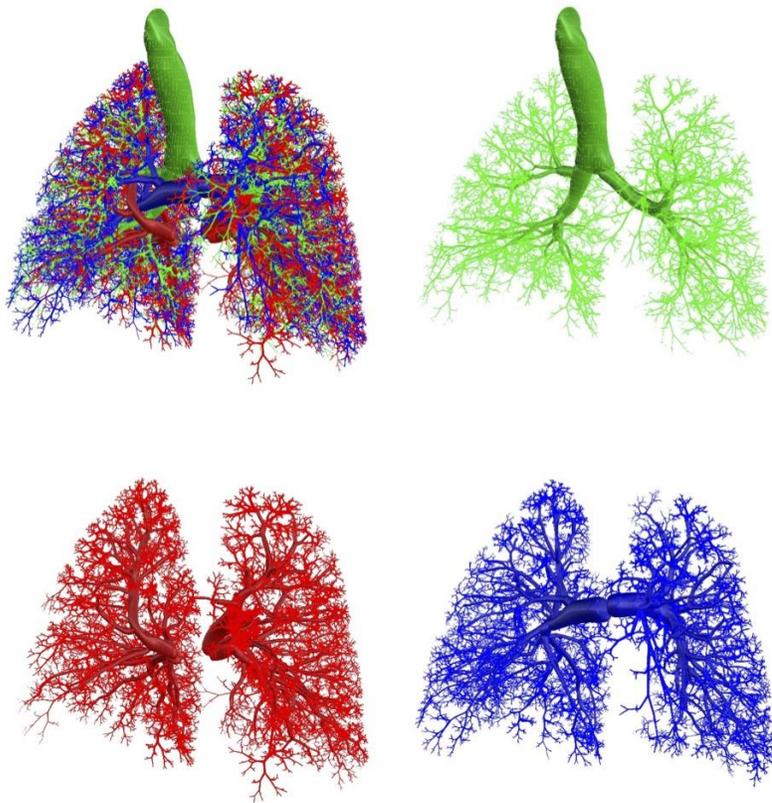


skeleton



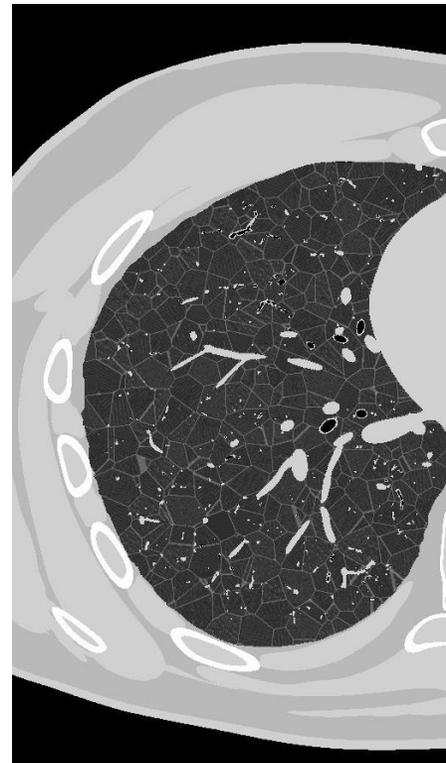


Non-parenchyma



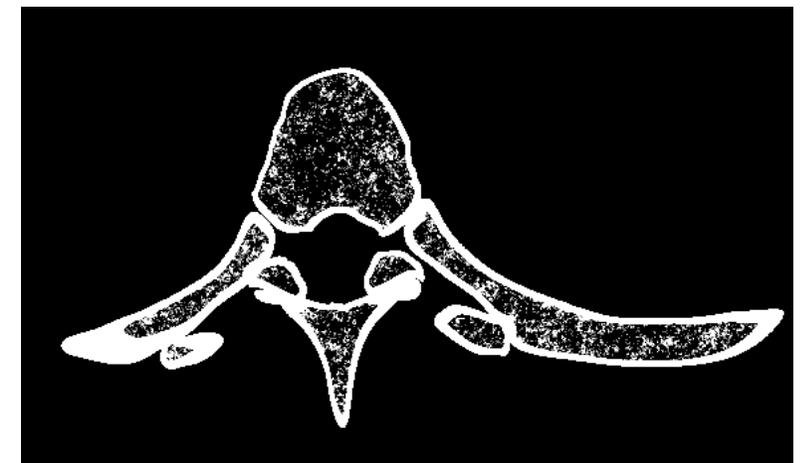
Abadi et al, IEEE TMI 2018

Parenchyma



Abadi et al, SPIE 2017

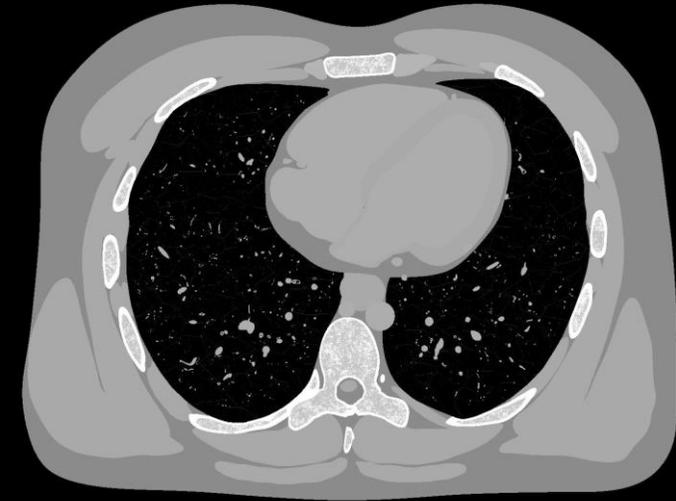
Bone



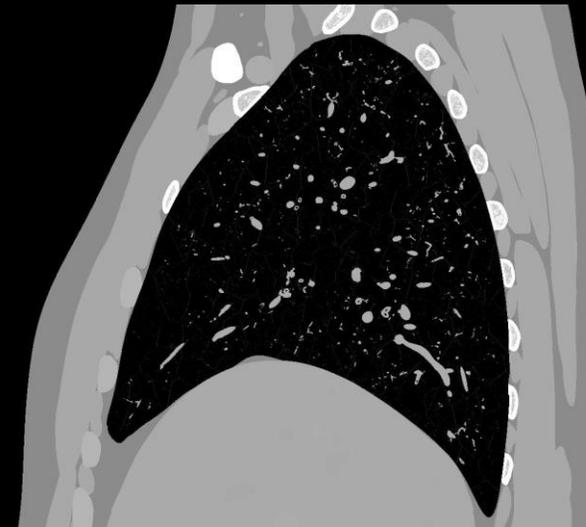
Abadi et al, IEEE TRPMS, 2018

4D high-resolution voxelized phantoms:

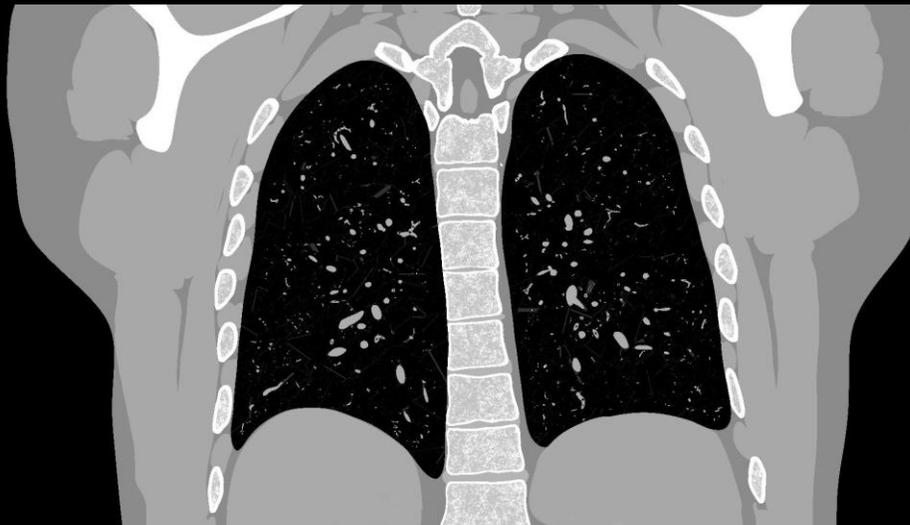
Axial



Sagittal



Coronal



t = 5 sec

t = 0 sec



X-ray detection: Photon-counting



Low imaging noise

Uniform energy response

Inherent spectral imaging

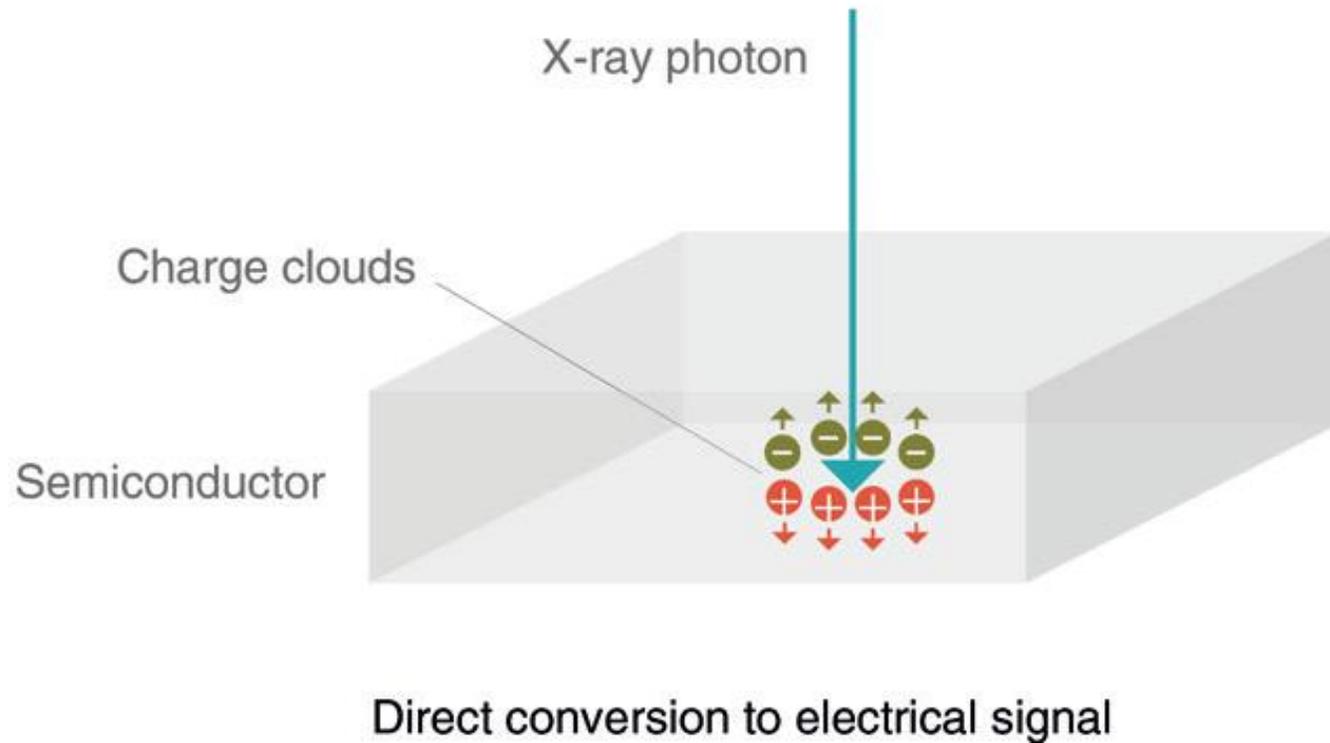
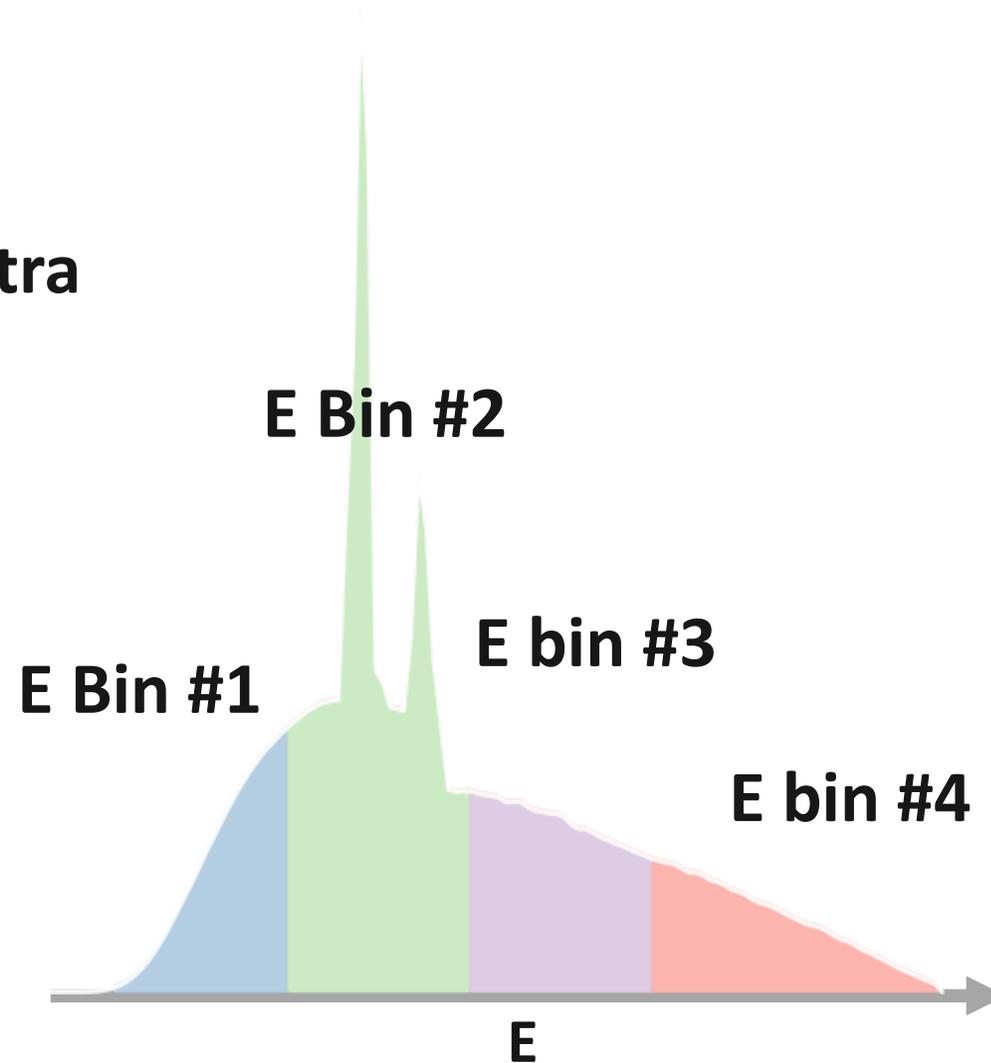


Image from Willemink et al, *Radiology* 2018



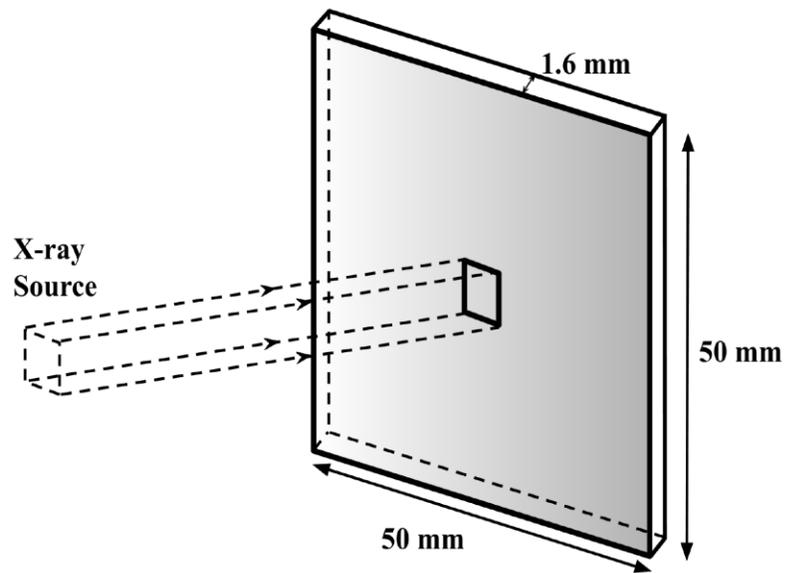
Polychromatic spectra from X-ray tube





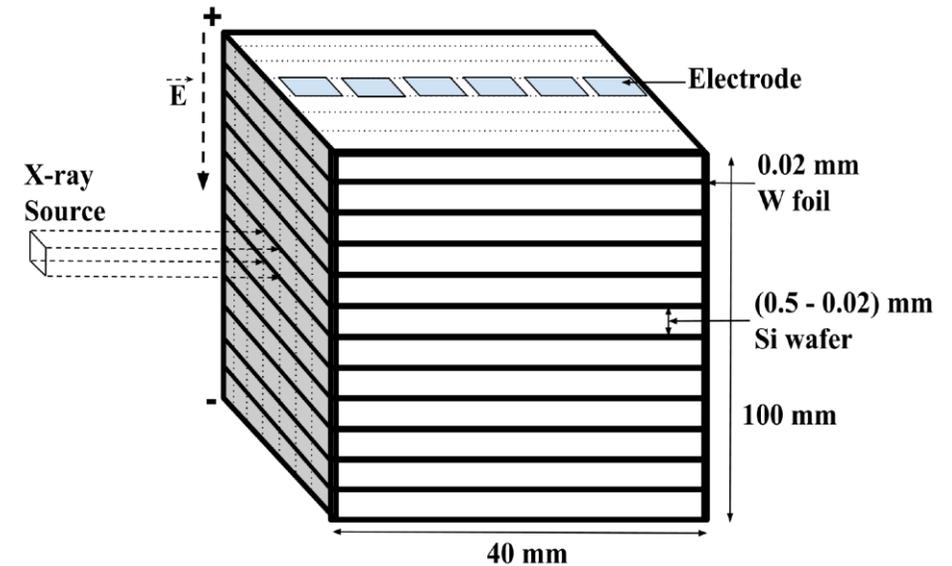
Face-on geometry

(high Z materials: CdTe, CdZnTe)



Edge-on geometry

(low Z materials: Si)

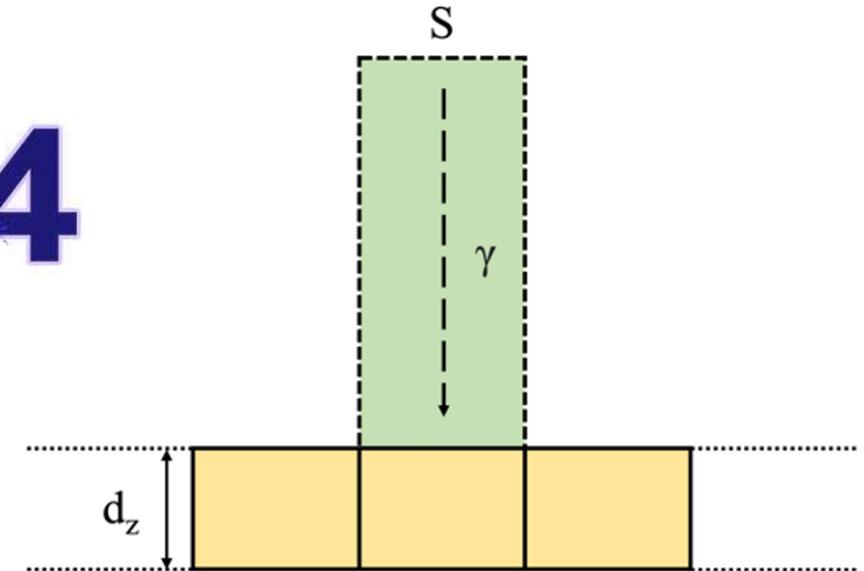




Monte Carlo model



- Stochastic X-ray interaction with detector bulk
 - an array of 100x100 pixels
 - the Livermore physics list
 - range cutoff 10 μm for CdTe and 1 μm for Si
 - 100 000 histories (or events) per run



-
- Energy and location of all interactions leading to energy depositions were saved in .txt file

Edep_keV	PositionX_	PositionY_mm	PositionZ_mm	DirectionX	DirectionY	DirectionZ	ParticleID	trackID	parentID	eventID	runID	processID
0.8093	-1.84707	-12.321	0.325	0	0	-1	0	1	0	274	0	1
0.75537	-1.84707	-12.321	0.305251	-0.227387	-0.383017	-0.895317	0	3	1	274	0	1
1.06706	-1.9216	-12.4465	0.0118099	-0.804098	-0.450616	-0.387779	-1	4	3	274	0	7
29.1733	-1.92188	-12.4467	0.01162	-0.583075	-0.677499	-0.44835	-1	4	3	274	0	6
1.195	-1.84707	-12.321	0.305252	-0.946756	0.260114	0.189719	-1	2	1	274	0	6
3.5354	-10.048	-5.83849	0.325	0	0	-1	0	1	0	346	0	1
0.484107	-10.048	-5.83849	0.310204	0.582625	0.506104	0.625012	1	2	1	246	0	7

- Modeling statistical and electronic noise
- Photon-counting (PC) detectors suffer from **charge sharing** between pixels and **pulse pileup** within the pixel.

Charge sharing model

$$\sigma = \sqrt{2 \frac{d_{iz} dkT}{eV} + \left(\frac{d_{iz} dNe}{10\pi\epsilon V} \right) \frac{1}{\sqrt{5}\sigma_i} + \sigma_i^2}$$

Initial charge cloud

Charge diffusion in the direction of electric field

Charge repulsion perpendicular to electric field

Pulse pile-up model

True count rate

Probability of m-th order pulse pile-up

$$N_{PPE}(E) = a \times \frac{1}{1 + a\tau} \times \sum_{m=0}^{\infty} (a\tau)^m \frac{e^{-a\tau}}{m!} \times \Pr(E|m)$$

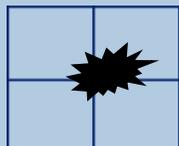
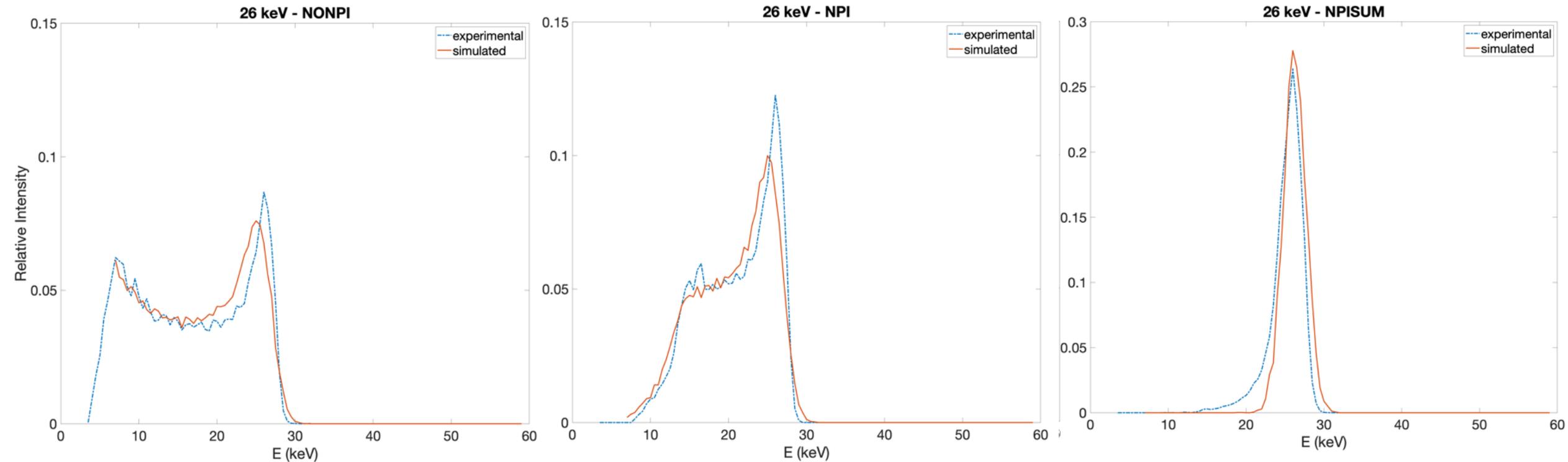
Probability of photons being recorded

Approach from Taguchi et al, *Med Phys* 2010

Validation – charge sharing



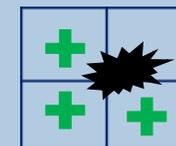
Charge sharing model was validated against experimental data obtained with monochromatic beam and CdTe PC detector in three different analog charge sharing (ACS) modes (62 x 62 x 650 μm).



No ACS correction applied

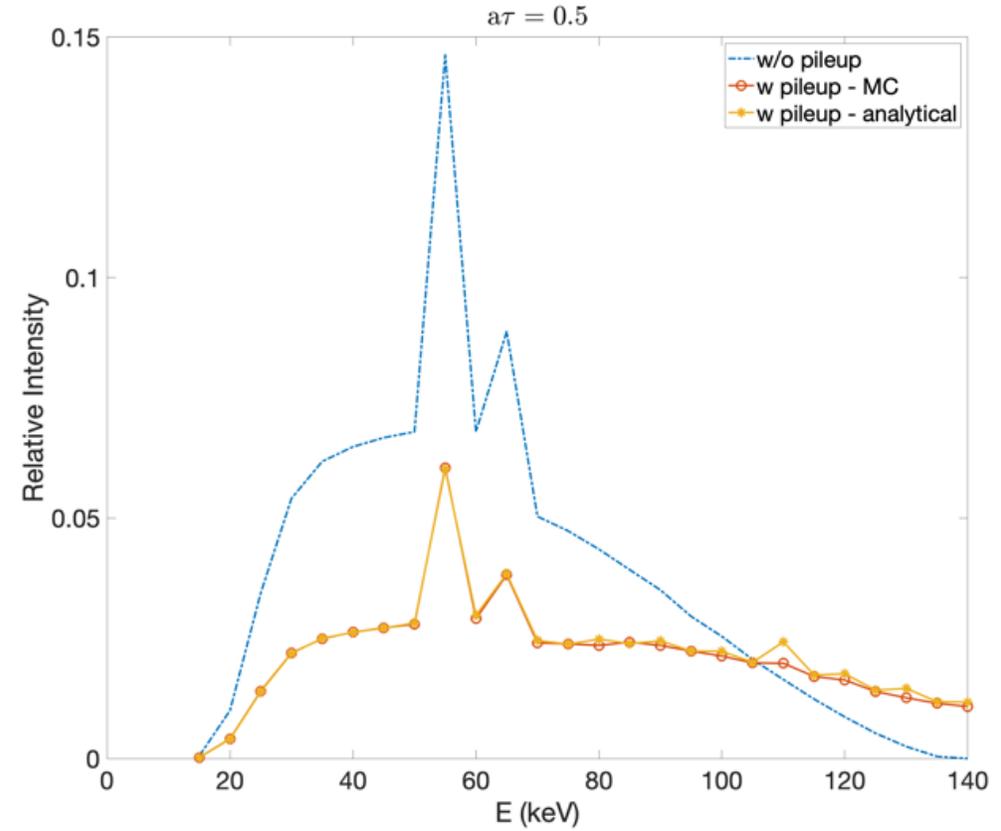
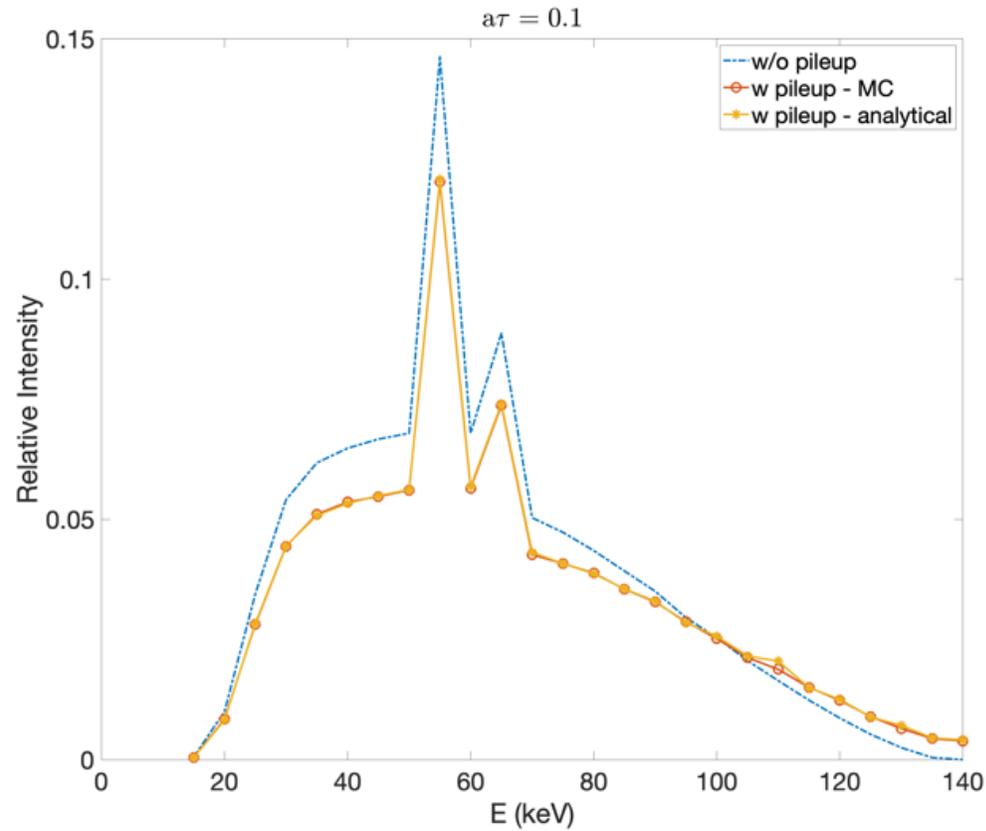


Neighbor Pixel Inhibit (NPI)
- removes multiple counts



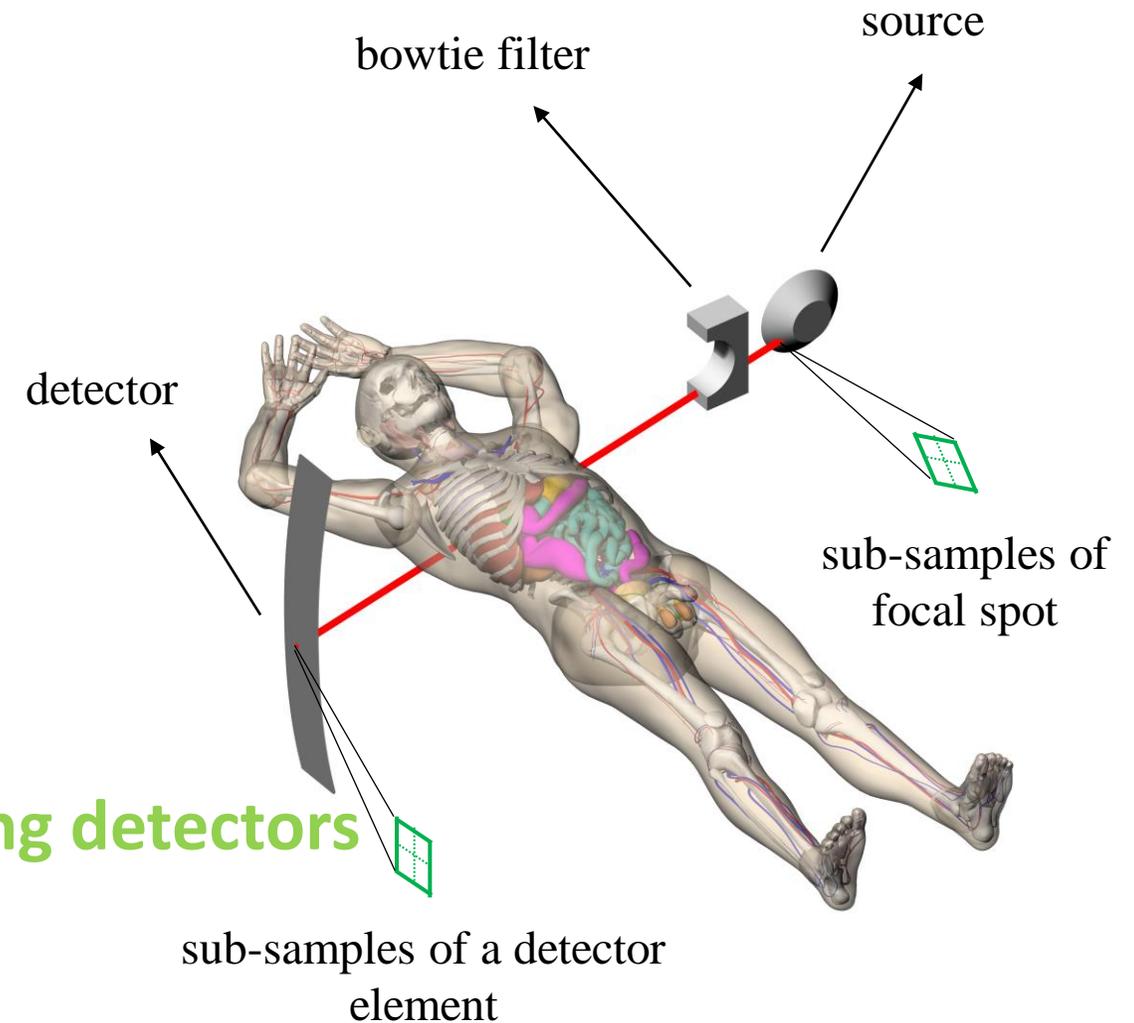
Neighbor Pixel Inhibit and
summing mode (NPISUM)
- recovers the charge spread

Validation – pulse pileup



Piled up photons registered as higher energy photon!

- **Scanner-specific or -generic:**
 - geometry, spectrum, bowtie filter, detector
- **Hybrid**
 - Ray-tracing and Monte Carlo modules
- **Tube current modulation**
- **Several tube voltage options**
- **Energy-integrating and photon-counting detectors**



XCAT: anthropomorphic chest phantom

Simulation output – CT scan

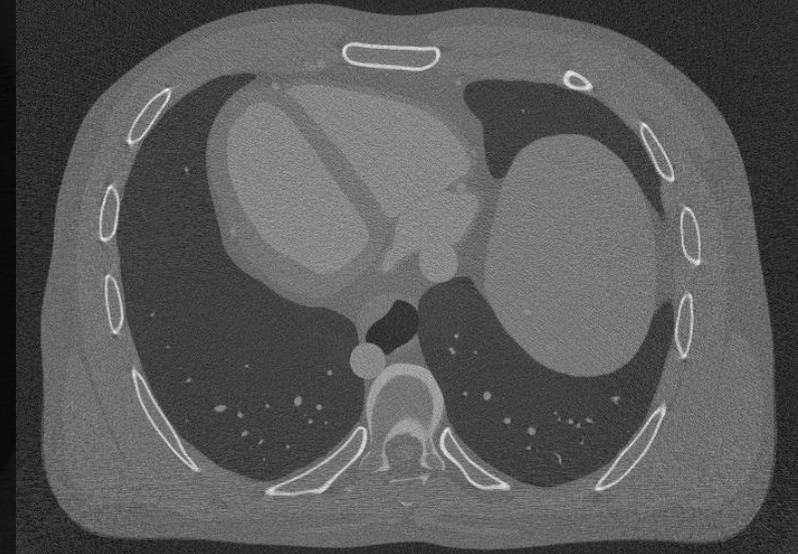
Primary signal



Primary + scatter signal



Primary + scatter signal + noise



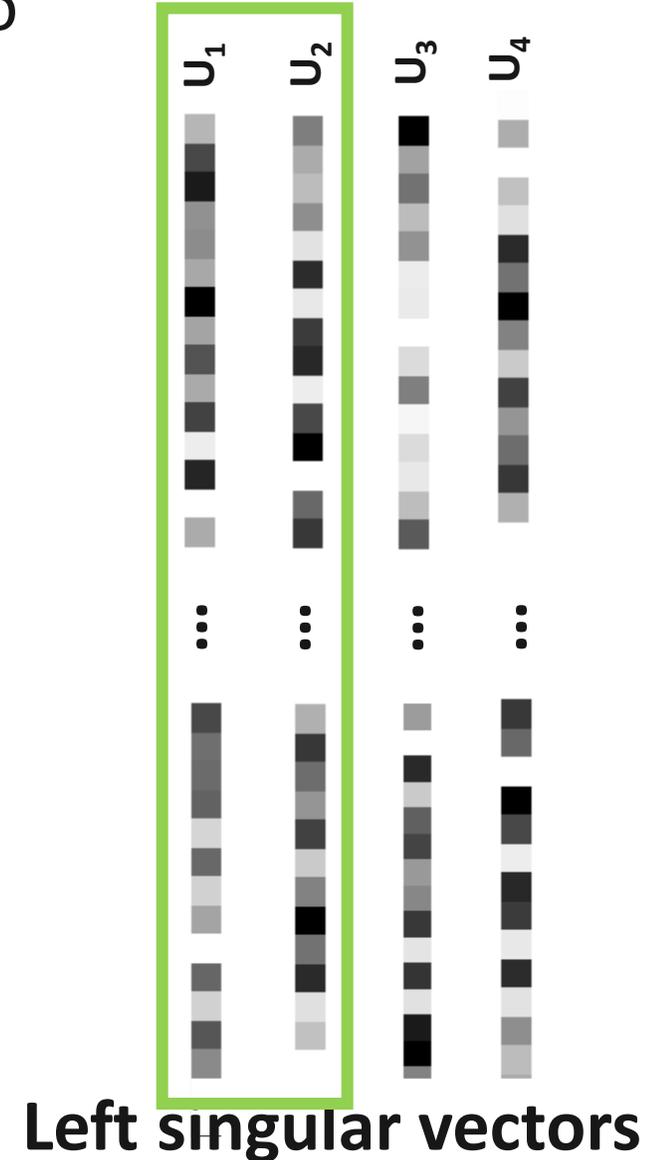
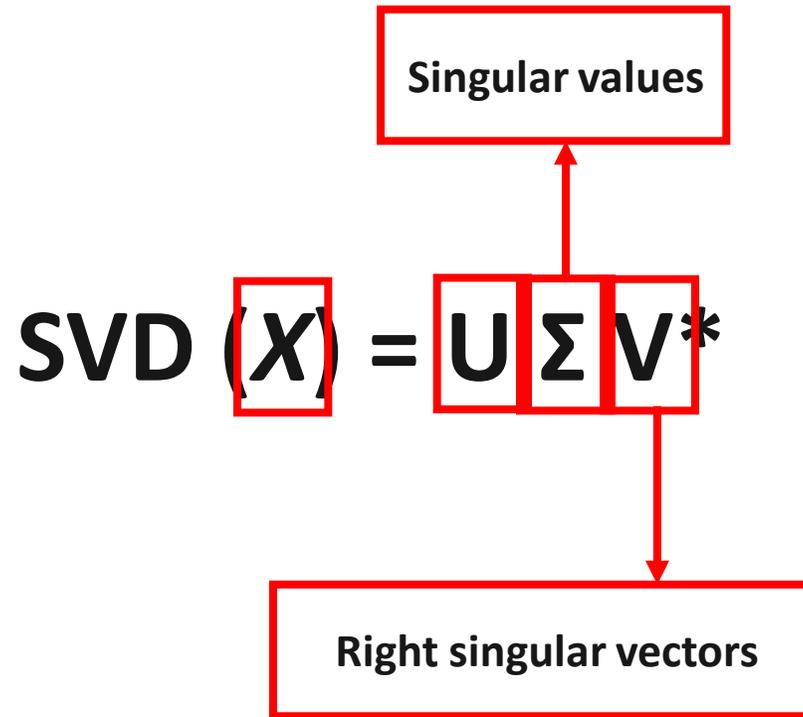
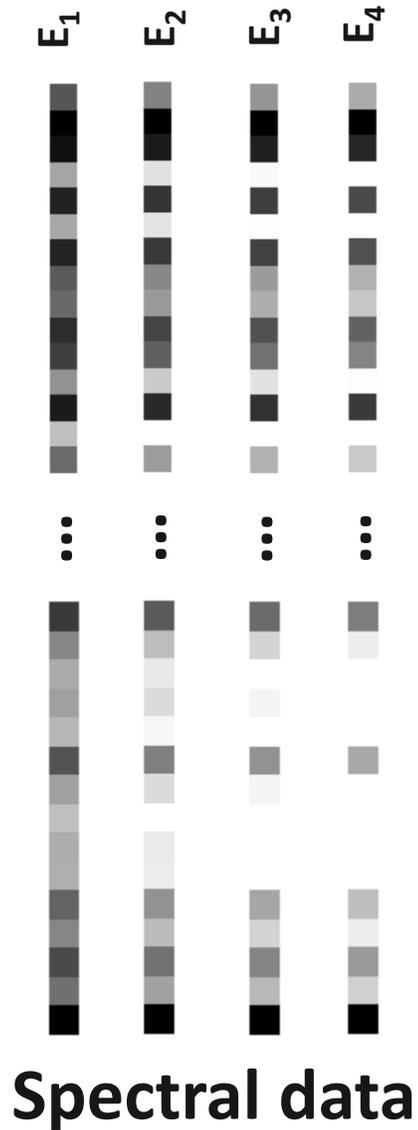
PART II

Machine learning in medical imaging - examples

Unsupervised model – SVD (PCA)



What is the main contribution to image formation?

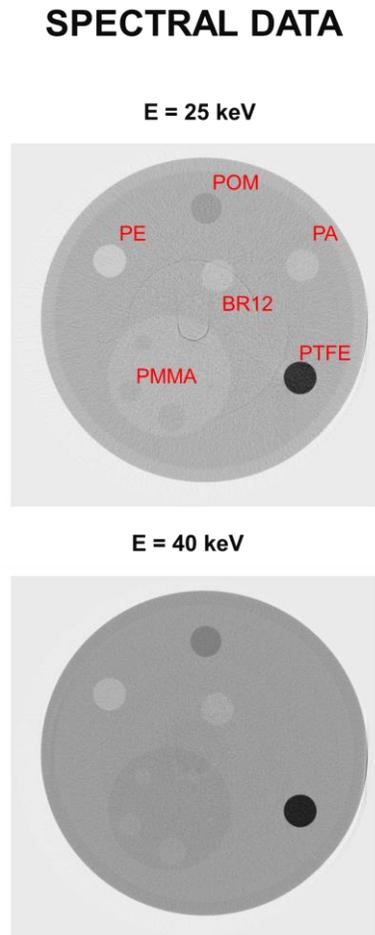


Beyond traditional radiology: ρ and effective Z



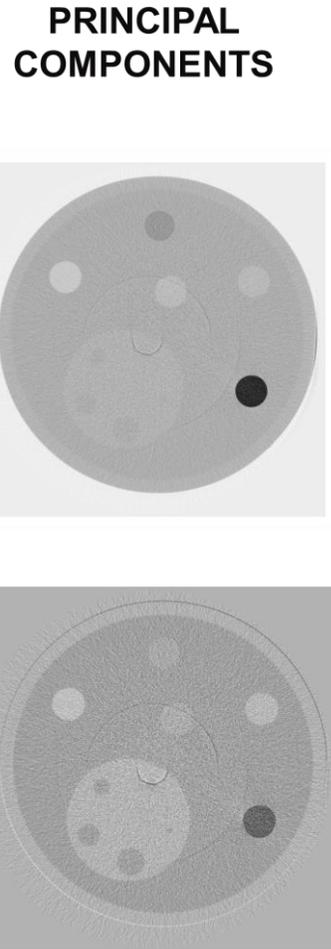
- Use spectral measurements to compute material properties.

CT scans with monochromatic
X-ray beams



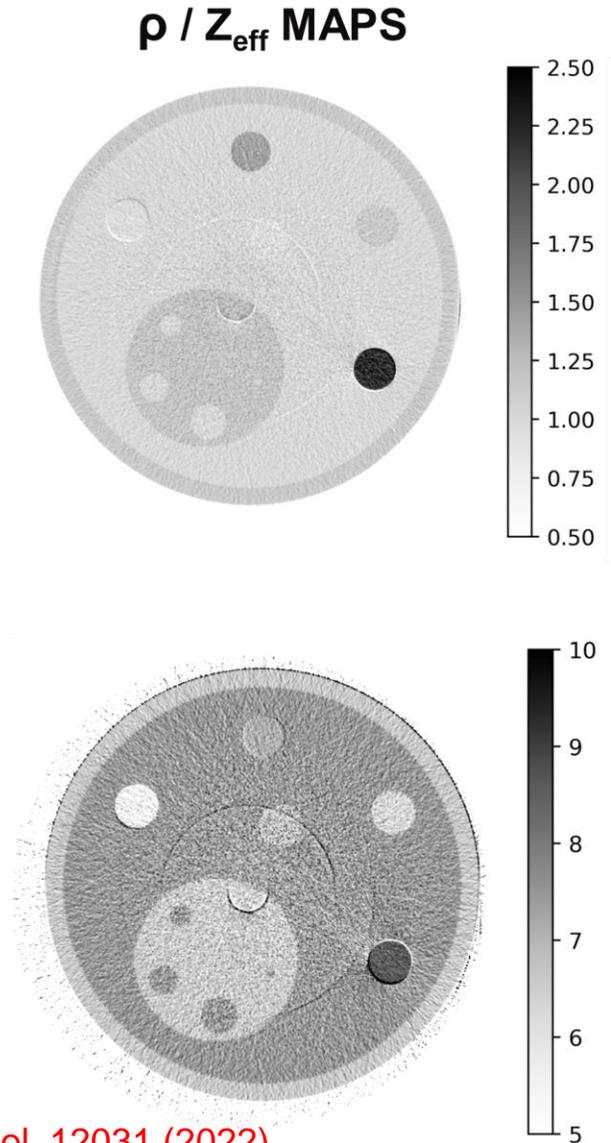
Photoelectric
contribution

Compton
contribution



Density

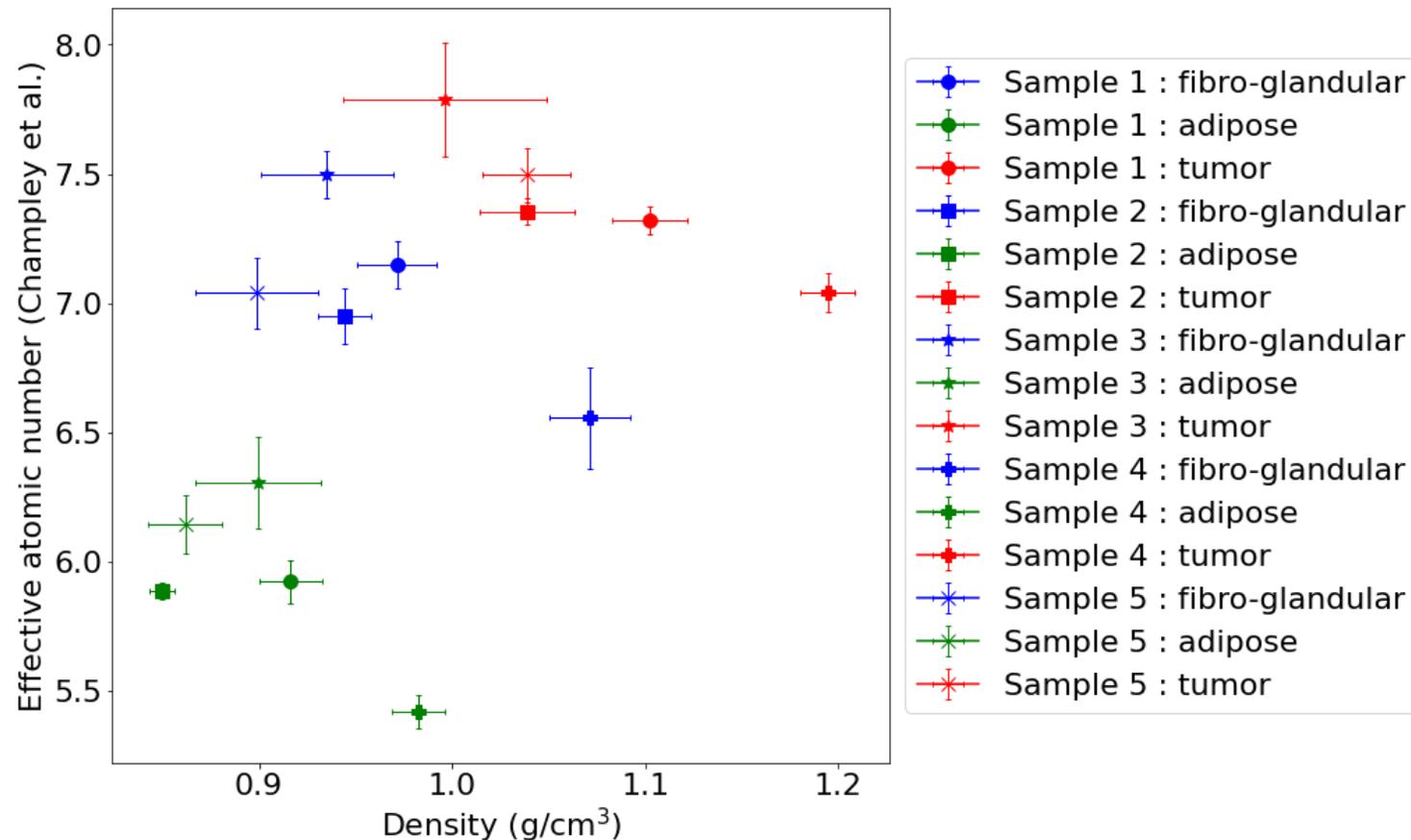
Effective Z



Why ρ/Z_{eff} ?



- Breast tissues can be better differentiated based on their density and effective Z, rather than using just gray levels.



Thank you!

Contact: stevan.vrbaski@phd.units.it

