Deep learning image reconstruction for positron emission tomography (PET): present status and future perspectives

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Overview

- **Brief review**
  - PET and image reconstruction
  - Deep learning (DL)
  - What does DL bring?
- **Main approaches**
  - Each makes varying use of data, imaging (& noise) models, existing algorithms
- **Recent directions**
  - Joint PET-MR reconstruction
  - Deep kernel representation
  - Dual-tracer imaging
- **Outlook**

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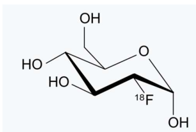
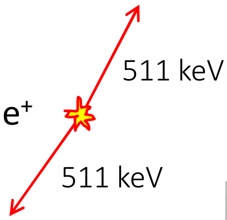
Positron emission tomography (PET)

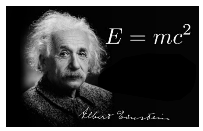
Used to image the brain, heart and body (e.g. dementia, heart disease, cancer)



$^{18}F \Rightarrow {}^{18}O + e^{+}$



Radiotracer is injected



PET scanner uses high-density crystals to detect the photon pairs

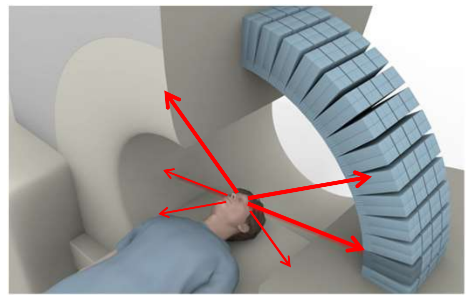


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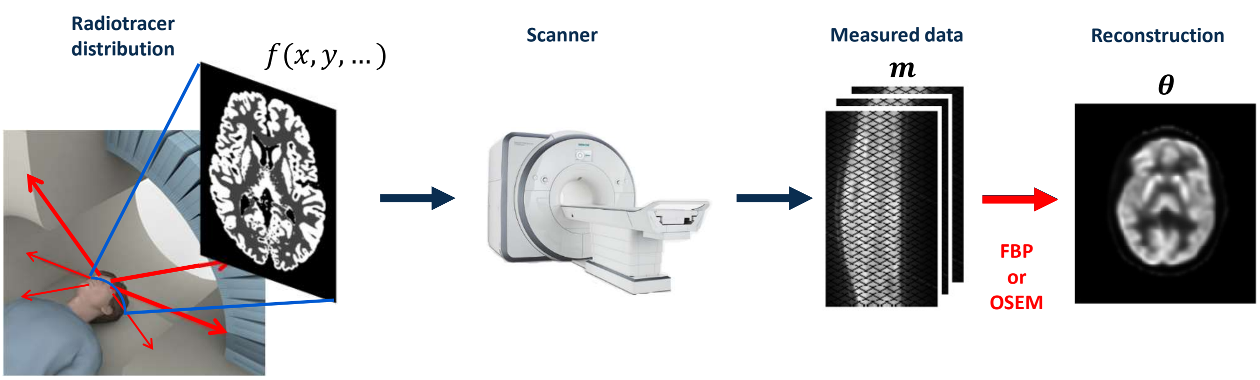
Image reconstruction



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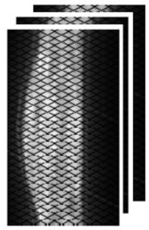
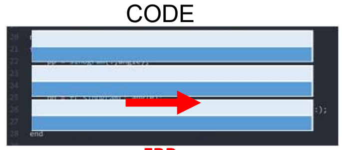
How to reconstruct

- Conventional: known input → code from known models → **find** output

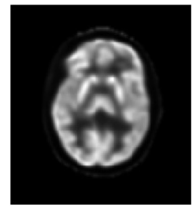
INPUT



CODE

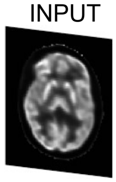


OUTPUT

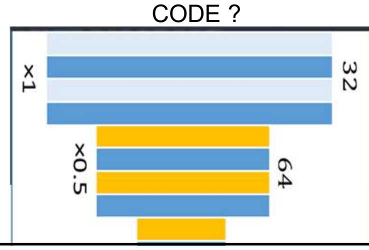


- Deep learning: known input → **find** *parameters* of general code → known output

INPUT



CODE ?



OUTPUT

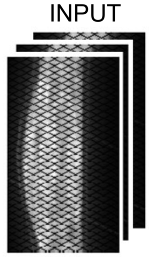
Healthy or unhealthy?

5

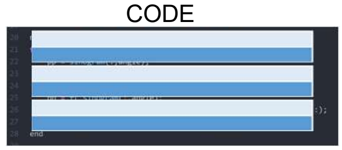
How to reconstruct

- Conventional: known input → code from known models → **find** output

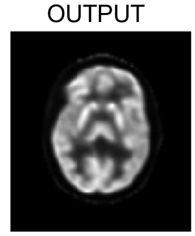
INPUT



CODE



OUTPUT



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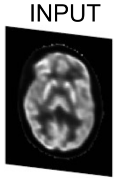
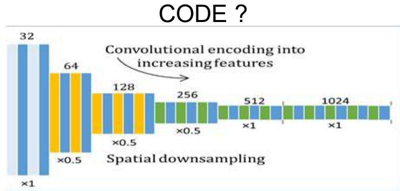
INPUT



CODE ?



OUTPUT

Healthy or unhealthy?

6

How to reconstruct

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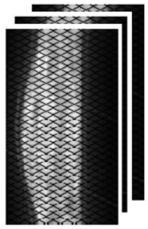
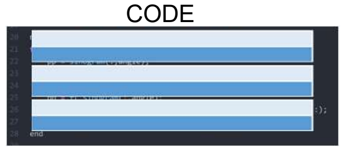
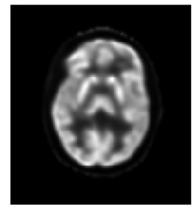
INPUT



CODE



OUTPUT



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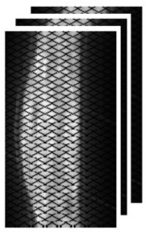

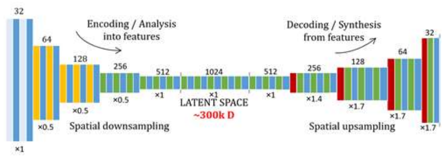

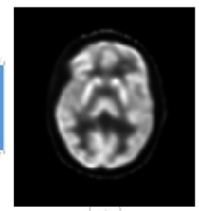

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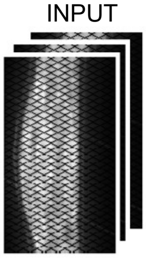
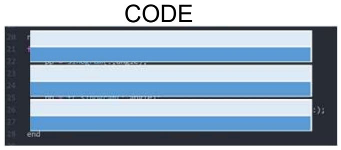
Ways of modeling

Generalisation
(out of distribution)

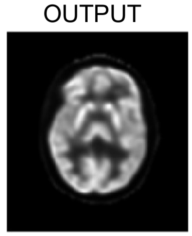
INPUT



CODE

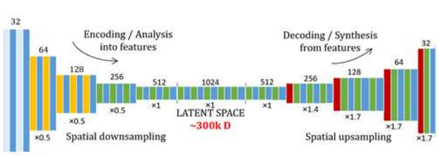


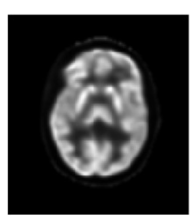
OUTPUT

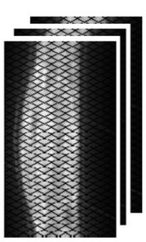


Radon (1887-1956)

Data







Maths,
Stats,
Physics,
...

Inductive prior
+
Data

Pure
data-
driven

Performance
(within distribution)

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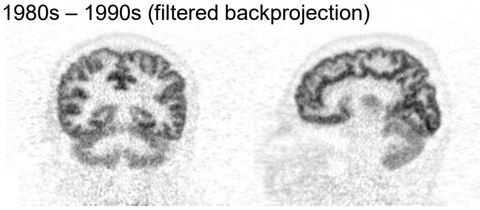
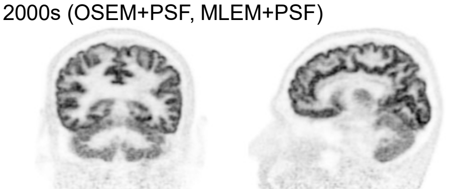
Using maths, stats and physics over the years…

1980s – 1990s (filtered backprojection)

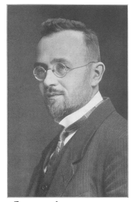


1990s (iterative reconstruction, OSEM, MLEM)

2000s (OSEM+PSF, MLEM+PSF)



Colsher 1980, Kinahan & Rogers 1989,
Shepp & Vardi 1982, Hudson & Larkin 1994



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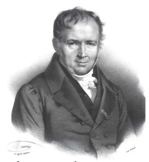
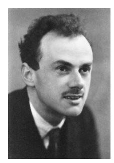
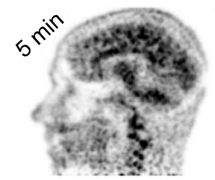


Poisson (1781–1840)



Paul Dirac (1902-1984)

Lower dose, or shorter scans:



Regularise (MAPEM)

MRI guidance

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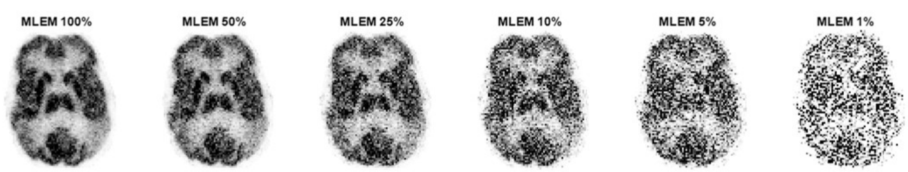
Kernel method for low dose [^{18}F]FDG (mMR)



Wang & Qi *IEEE TMI* 2015
Bland …., Reader *IEEE TRPMS* 2017

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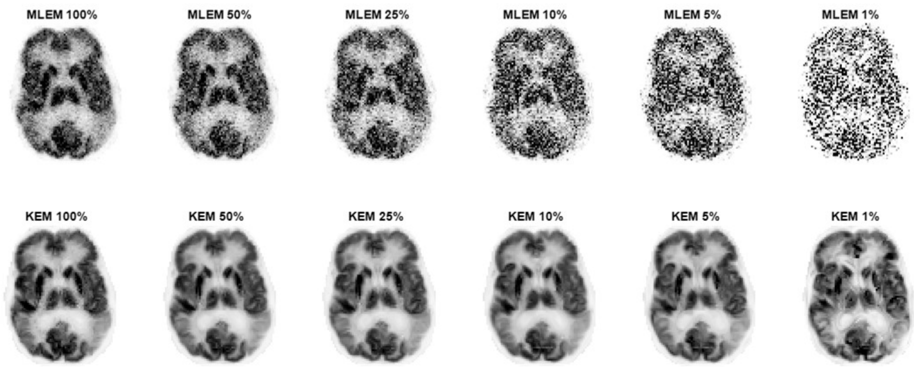
Kernel method for low dose [^{18}F]FDG (mMR)



Wang & Qi *IEEE TMI* 2015
Bland …., Reader *IEEE TRPMS* 2017

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So why use deep learning?

- Conventional reconstruction
  - Fits to noisy data → noisy images
  - Noise compensation (regularisation) is either simple (quadratic, TV, RDP, …)
    … or assumes how to best exploit multi-modal information (e.g. MRI)
- Assumes
  - Imaging system model
  - Data noise distribution
  - How to regularise

… but do we really know these things?

- Deep learning uses
  - Real-data examples to learn
    - more accurate imaging and noise models (and their 'inverse')
  - Ground truth or high-quality reference data
    - to learn how to regularise images

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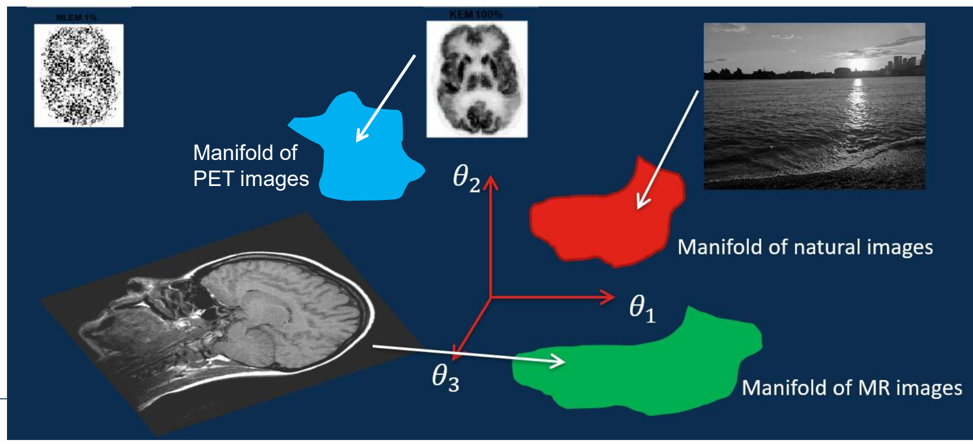

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DL in PET reconstruction

1. Direct (e.g. DeepPET, AUTOMAP, …)
use mainly data

2. Direct with physics (e.g. LPD)
use data as well as our imaging (& noise) model

3. Unrolled iterative reconstruction (e.g. FBSEM-Net)
use known reconstruction algorithms
imaging model and noise model
and data

4. DL representations (e.g. DIP)
no need for training data

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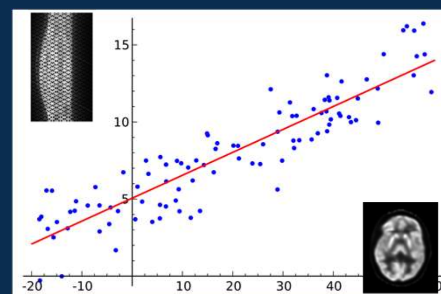
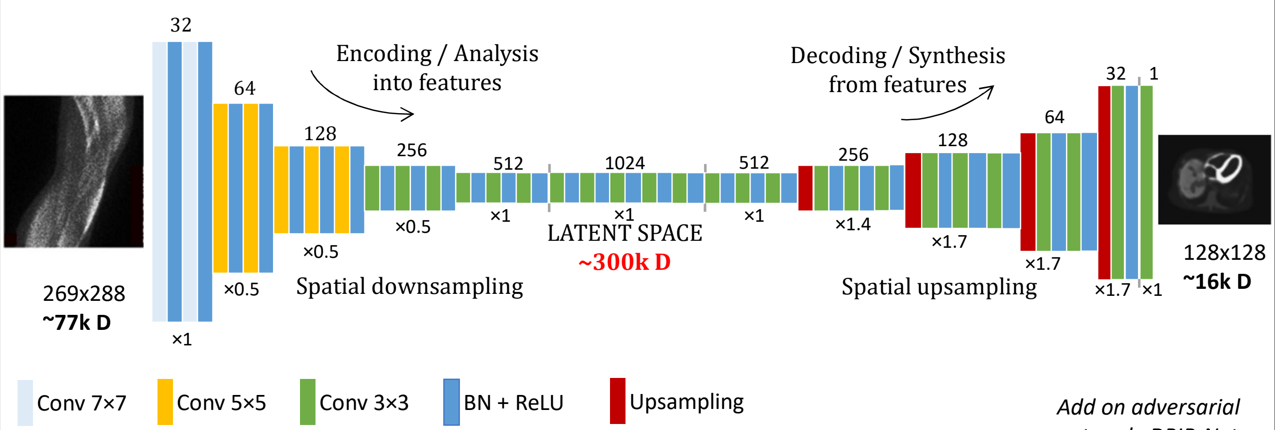
Direct reconstruction with DL



Direct DL reconstruction from sinograms: DeepPET



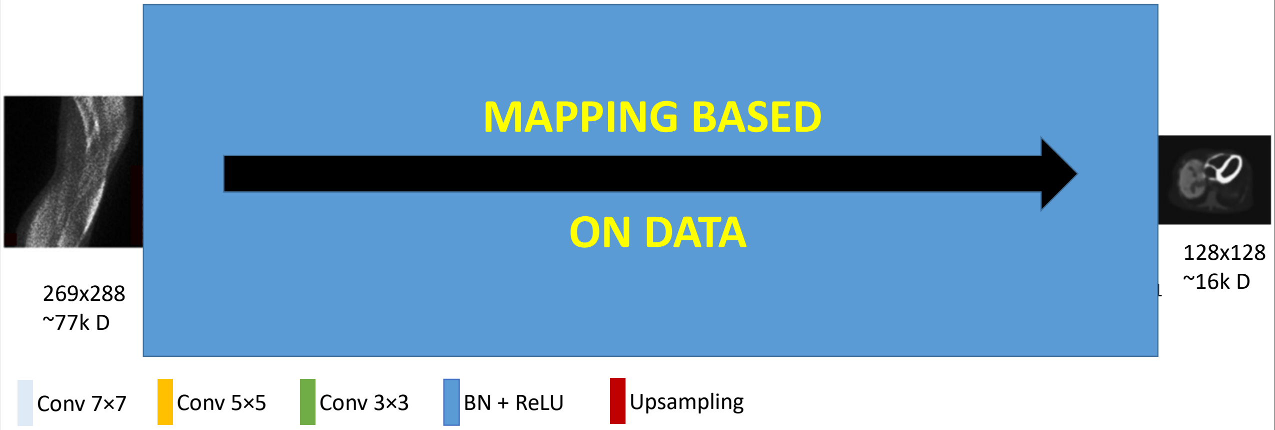
Add on adversarial network: DPIR-Net Hu et al, TRPMS 2020

Convolutional encoder decoder:

- **200,000 simulated training data pairs** to learn **~60 million parameters** via MSE loss
- (Simple linear mapping would need > 1 billion parameters)

Figure represents method of Häggström *et al*, MIA 2019

Direct DL reconstruction from sinograms: DeepPET



Convolutional encoder decoder:

- **200,000 simulated training data pairs** to learn **~60 million parameters** via MSE
- Note a simple linear mapping would need > 1 billion parameters

Figure represents method of Häggström *et al*, MIA 2019

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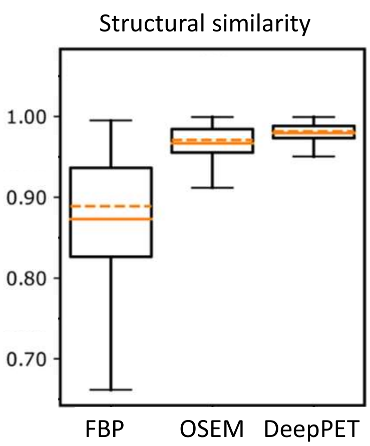
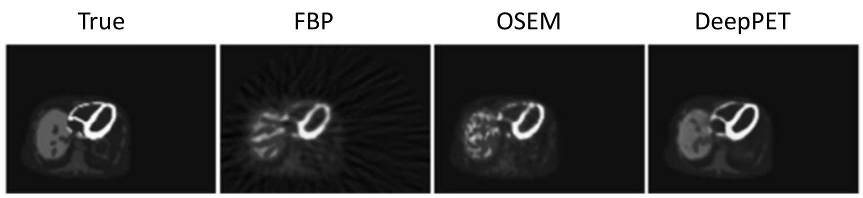
DeepPET: results

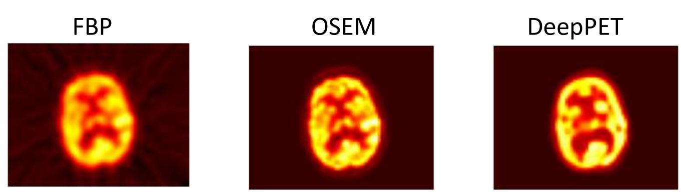
Simulated data





✓ **Within distribution**

Real data



- **Outside distribution**

~10% lower noise (RMSE) than OSEM conventional reconstruction
~100x faster than OSEM

Häggström *et al*, MIA 2019

+discriminator, perceptual loss, DPIR-Net: Zhanli Hu et al, IEEE TRPMS (5) Jan 2021

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Direct DL reconstruction summary

Examples: DeepPET, DPIR-Net, AUTOMAP, …

Häggström *et al*, MIA 2019, Zhanli Hu *et al*, IEEE TRPMS (5) Jan 2021, Zhu *et al* Nature 2018

- ✓ Few model assumptions (less modeling error)
- ✓ Data driven, just the network's inductive prior
- ✓ Fast reconstructions

- Slow training
- **Huge data needs** (>>10k data pairs)
- Relearns physics & statistics
- Huge network (10-100 million parameters, just for 2D)
- Applied for **2D reconstruction**, not yet fully 3D
- Generalisation / outside training distribution?
- Stability? Antun *et al*, PNAS 2020

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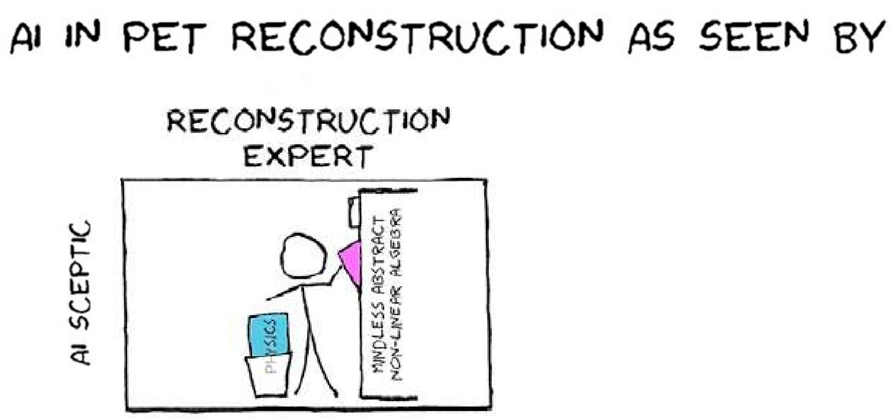

Journal of Nuclear Medicine October 2021, 62 (10) 1330-1333; DOI: https://doi.org/10.2967/jnumed.121.262303

HOT TOPICS

Artificial Intelligence for PET Image Reconstruction

Andrew J. Reader[1] and Georg Schramm[2]

[1]*School of Biomedical Engineering and Imaging Sciences, King's College, London, United Kingdom; and* [2]*Division of Nuclear Medicine,*

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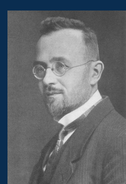
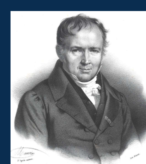
Iterative reconstruction with DL



Radon (1887-1956)



Poisson (1781–1840)

Data

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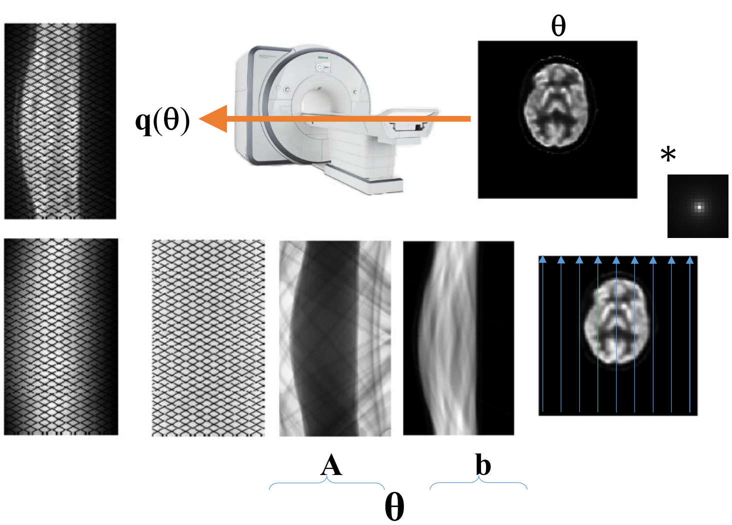
Physics modelling of a PET acquisition



$\boldsymbol{P}$: positron range
$\boldsymbol{X}$: Radon transform
$\boldsymbol{L}$: attenuation factors
$\boldsymbol{N}$: normalisation related factors

$\boldsymbol{s}$: scatter
$\boldsymbol{r}$: randoms

$$\mathbf{q}(\boldsymbol{\theta}) = \mathbf{A}\boldsymbol{\theta} + \mathbf{b}$$

$\boldsymbol{A}$: forward projection, FP
$\boldsymbol{A}^{\boldsymbol{T}}$: backprojection, BP

For MRI: image -> coil sensitivity maps -> FFT -> undersample: $\boldsymbol{q}(\boldsymbol{\theta}) = \boldsymbol{UFC\theta}$

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Embedding deep learning into iterative reconstruction

Unrolled iterative methods:
- ✓ Iterative reconstruction uses objectives with physics and stats modelling and theoretically convergent algorithms
- ✓ use DL for the prior (the image manifold)

Compared to direct DL
- ✓ **Practical for 3D**
- ✓ **Reduced** training **data** needs (~*tens* of 3D images)
- ✓ Expect improved generalisation outside the training distribution

- **Examples**
  - Lim *et al* 2018 (BCD-Net for low count PET), TMI 2020 (Iterative NN)
  - Gong *et al* 2019 (MAPEM-Net)
  - Mehranian and Reader 2020 (FBSEM-Net)
  - Rui Hu, Huafeng Liu 2022 (TransEM)

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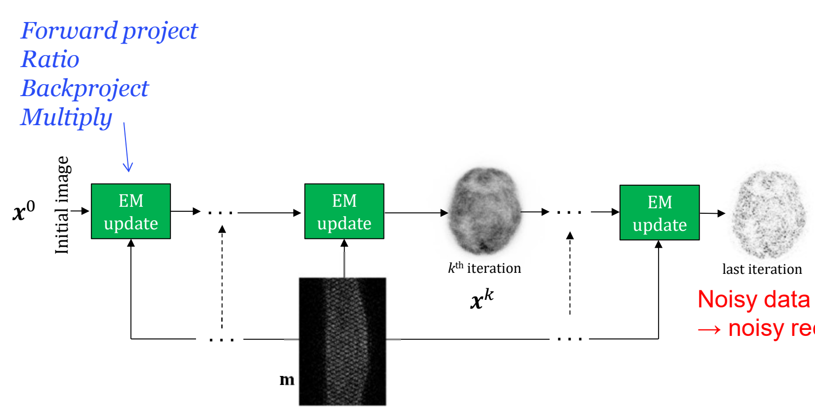
Conventional ML-EM (and OSEM)

$$\boldsymbol{x}^{n+1} = \frac{\boldsymbol{x}^n}{\boldsymbol{A}^T\boldsymbol{1}}\boldsymbol{A}^T\left(\frac{\boldsymbol{m}}{\boldsymbol{A}\boldsymbol{x}^n + \boldsymbol{\rho}}\right)$$

Iterative reconstruction unrolled into a deep network:



Noisy data (time, dose, scanner)
→ noisy reconstructions

Unrolling iterative recon: Gregor & LeCun 2010

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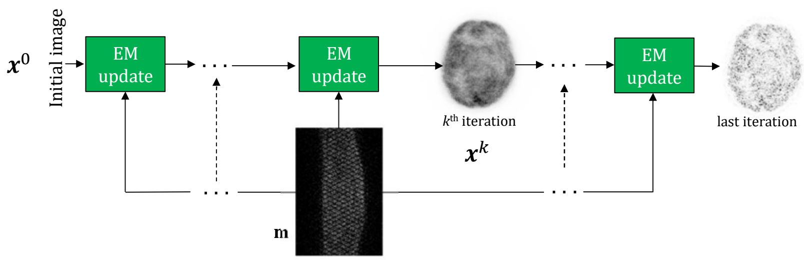
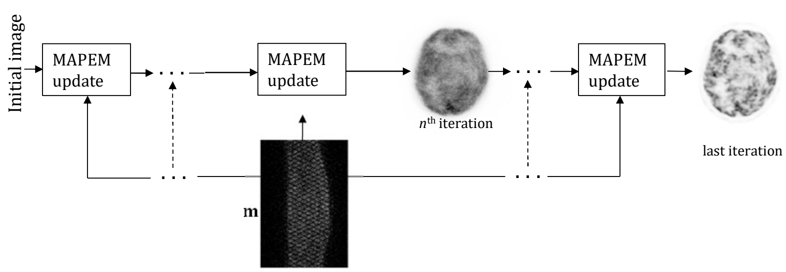
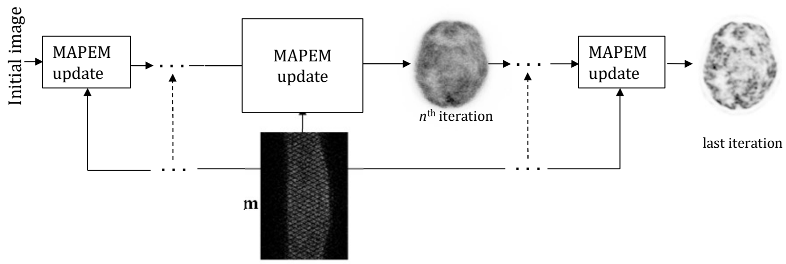

x^0
Initial image
EM update
EM update
EM update
k^{th} iteration
x^k
last iteration
m

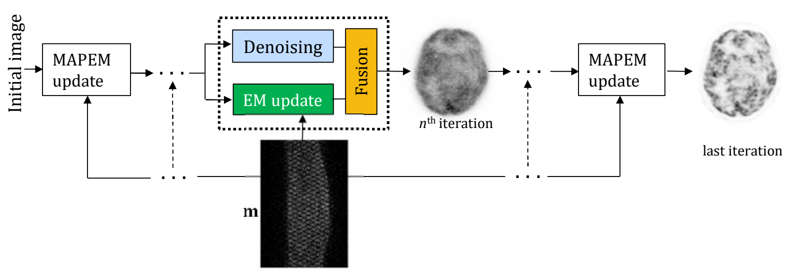
25


Initial image
MAPEM update
MAPEM update
MAPEM update
n^{th} iteration
last iteration
m

26


Initial image
MAPEM update
MAPEM update
nth iteration
MAPEM update
last iteration
m

27


Initial image
MAPEM update
Denoising
EM update
Fusion
nth iteration
MAPEM update
last iteration
m

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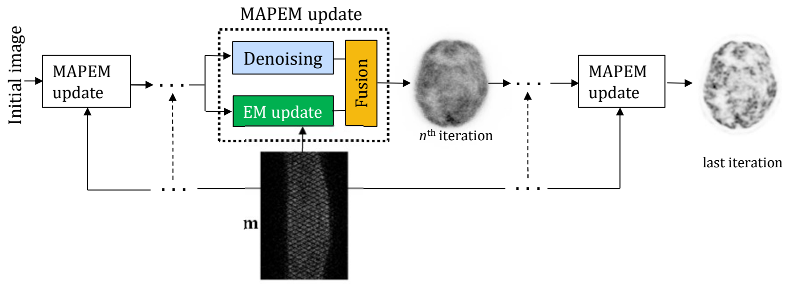
Example of PET regularisation



Mathematically convenient
(e.g. quadratic prior)

Unlikely to be optimal

De Pierro TMI 1995

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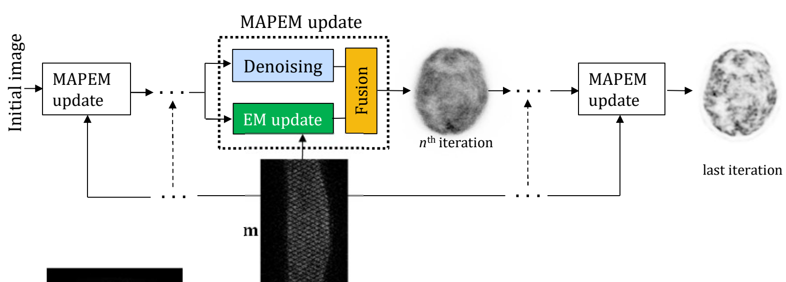
Example of PET regularisation



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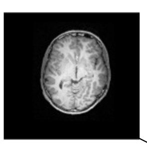
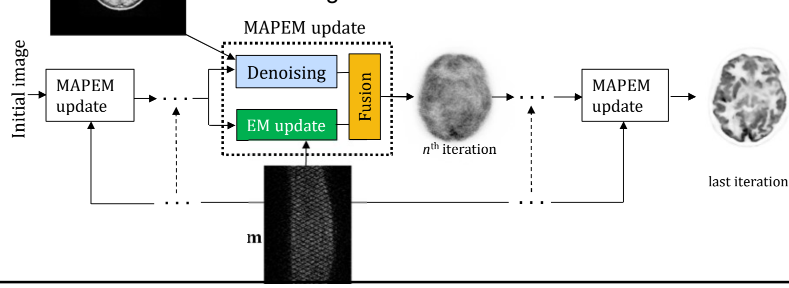


Can use MR to guide the denoising



How much MR guidance?

Unlikely to be optimal

…use deep learning

Bowsher IEEE NSS MIC 2004

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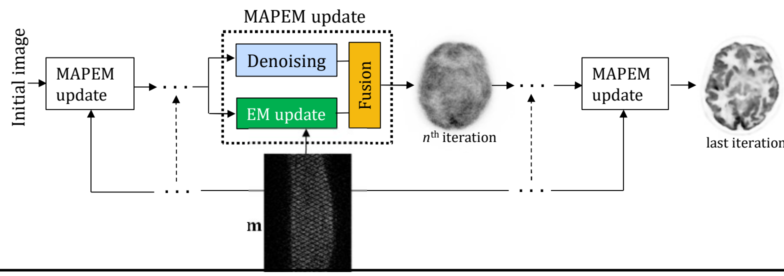
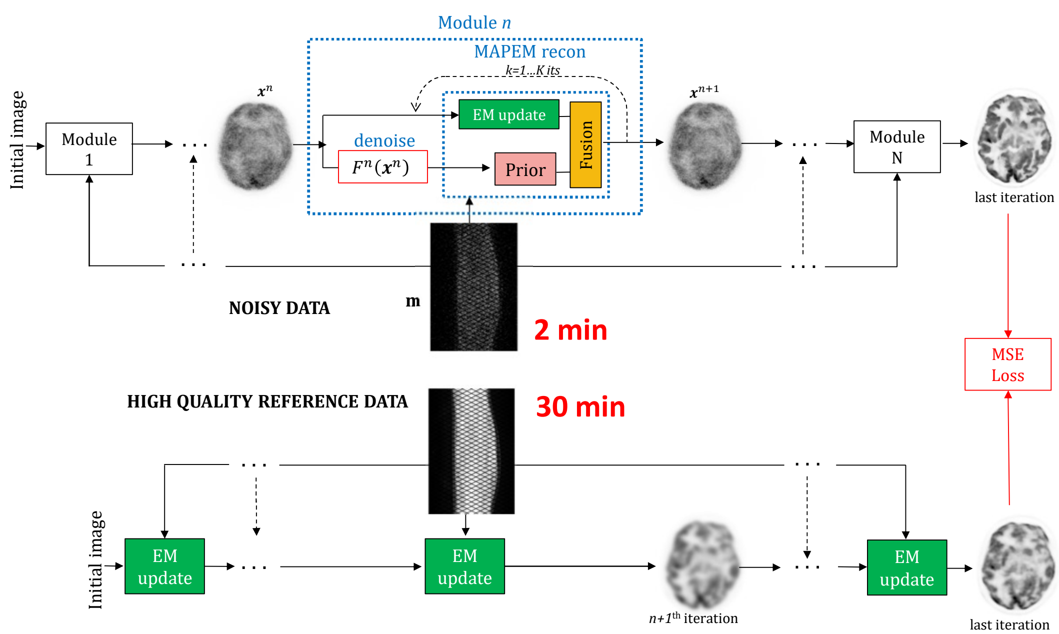


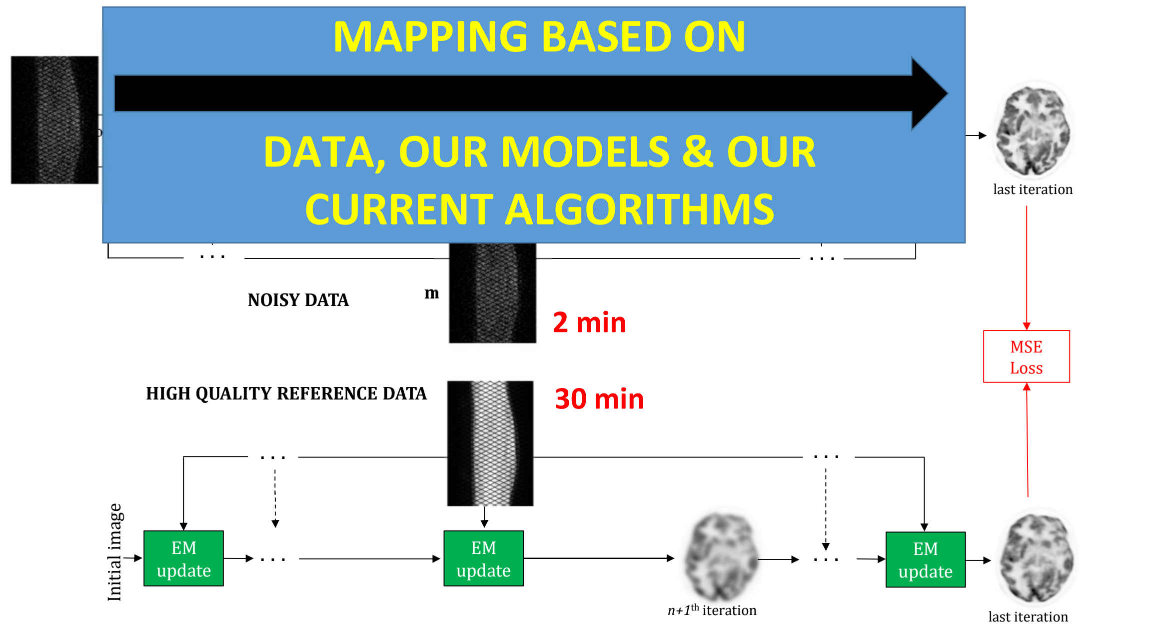
31

DL unrolled reconstruction for 3D PET



32

DL unrolled reconstruction for 3D PET



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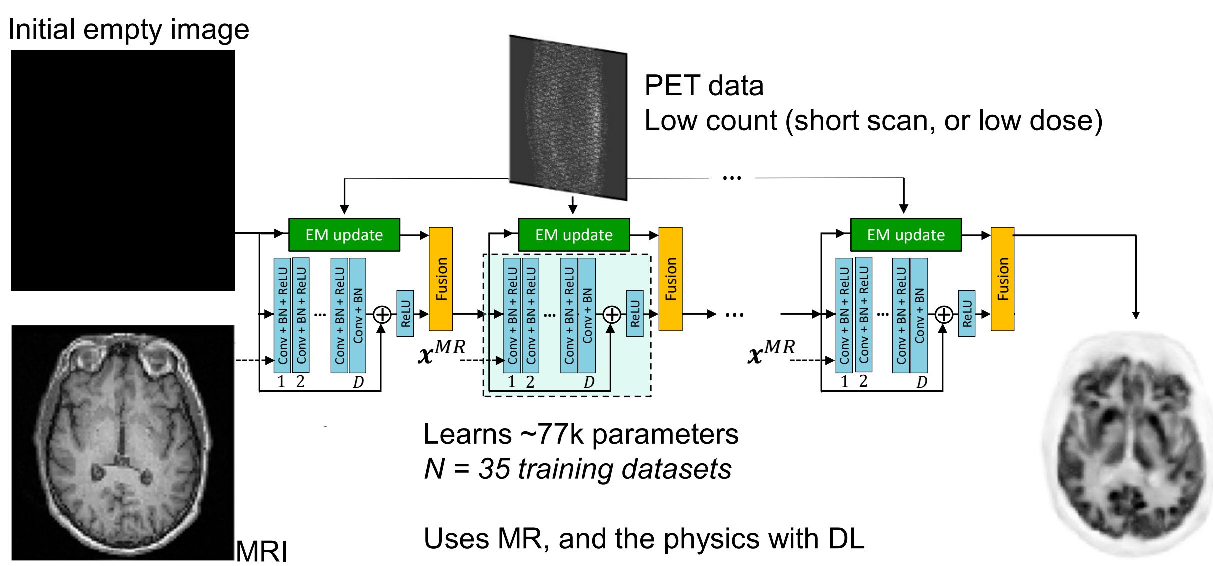
FBSEM-Net: real [^{18}F]FDG data



Learns ~77k parameters
N = 35 training datasets

Uses MR, and the physics with DL

Reconstructed image of [^{18}F]FDG

Mehranian and Reader, IEEE TRPMS 2020

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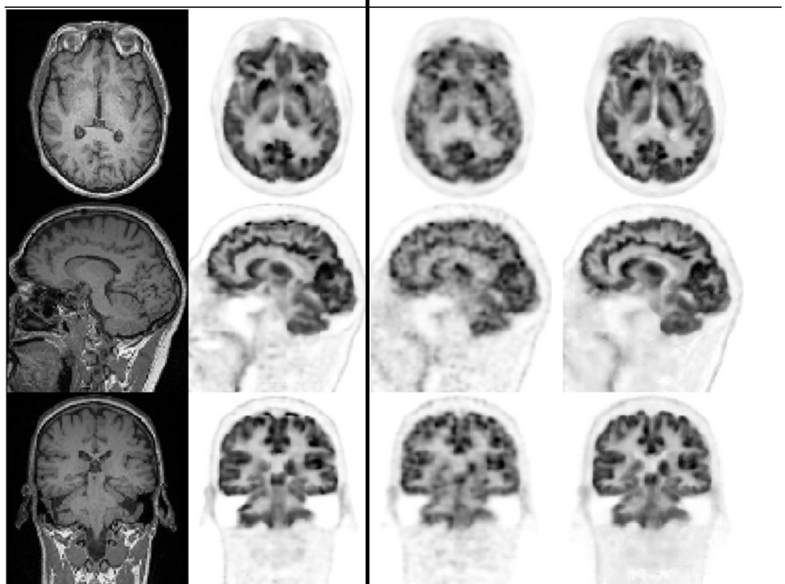
FBSEM-Net: real [^{18}F]FDG data

Uses MRI and AI

MRI | Reference | OSEM | FBSEM-Net



Mehranian and Reader, IEEE TRPMS 2020

30 min | **2 min**

Recent variations:

Sequential training
[Corda d'Incan et al
IEEE TRPMS 2021]

Using **transformers**
[Rui Hu, Huafeng Liu
2022]

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Unrolled reconstruction summary

- ✓ Use known physics, statistics, trusted algorithms for reconstruction
- ✓ Exploit training data to define the image manifold
- ✓ Fewer trainable parameters (e.g. ~77k)

  Smaller training sets (e.g. ~35), improved generalisation
- ✓ Practical for 3D reconstruction

- Slower than direct reconstruction

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Some recent directions

Joint PET-MR reconstruction

Multiplexed PET

Deep kernel

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Joint PET-MR reconstruction

- Motivation
  - Exploit similar information during reconstruction
  - …before noise (PET) or undersampling (MR) effects otherwise appear in independent reconstructions
  - Hence seek to outperform reconstructions with fixed guidance images
- Challenges
  - Guidance is wrong where structures (edges) differ between modalities
  - Need a joint prior for reducing noise and improving resolution for common structures, while preserving modality-unique information

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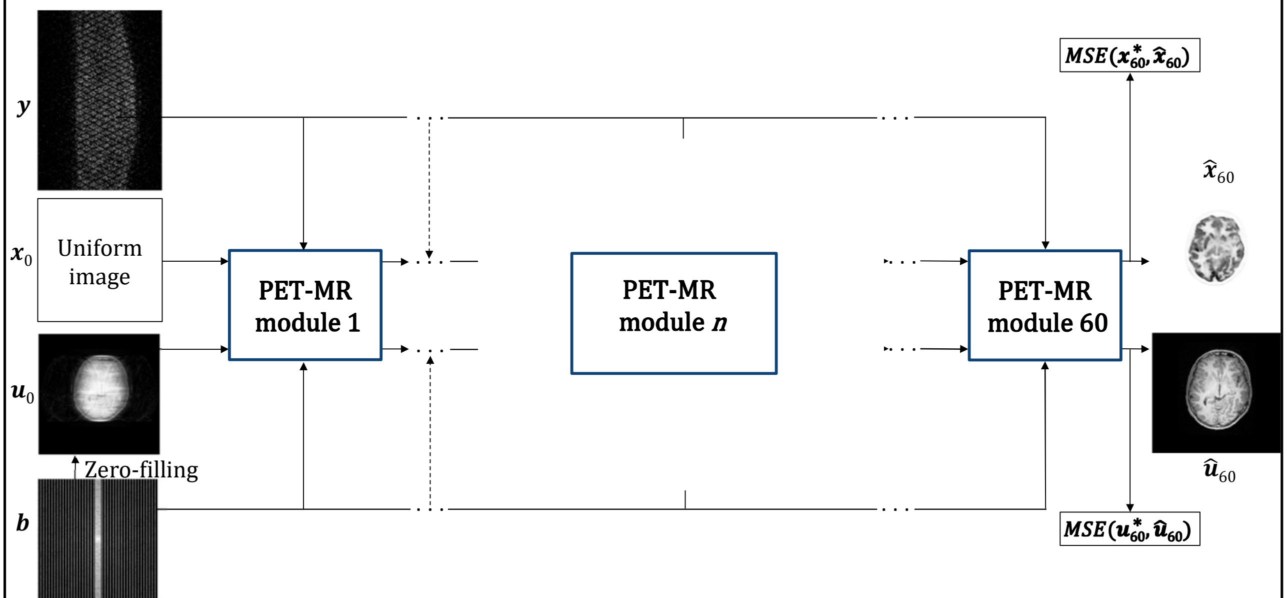
Joint DL PET-MR Reconstruction



Corda D'Incan, Schnabel and Reader, IEEE Medical Imaging Conference (Milan, Italy) 2022

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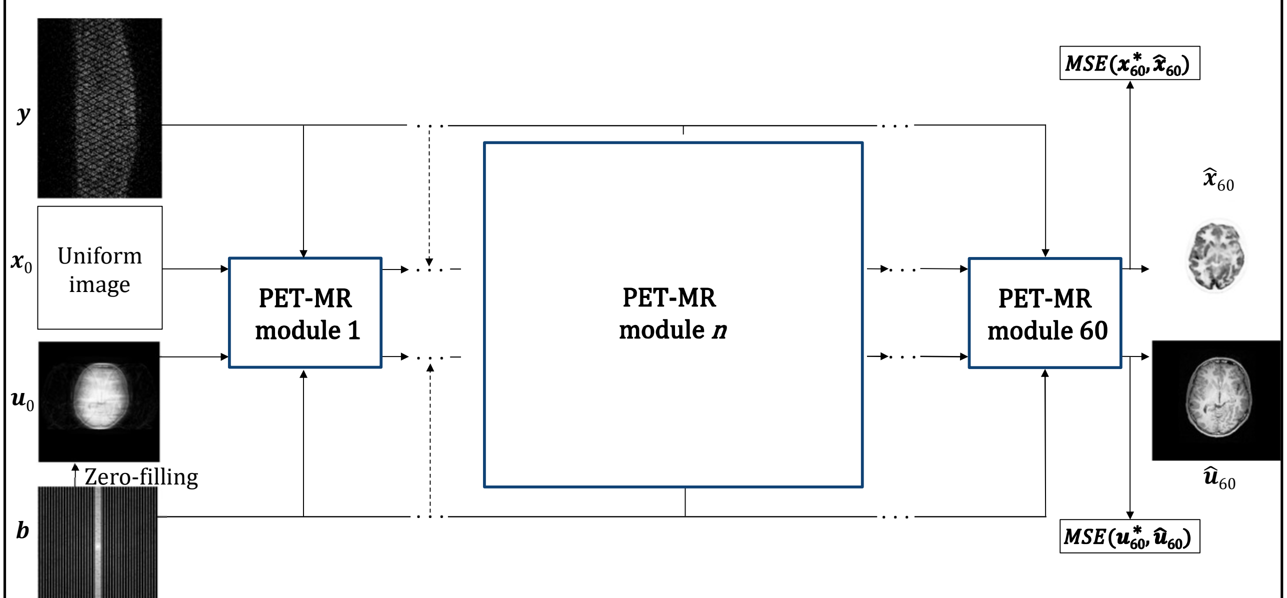
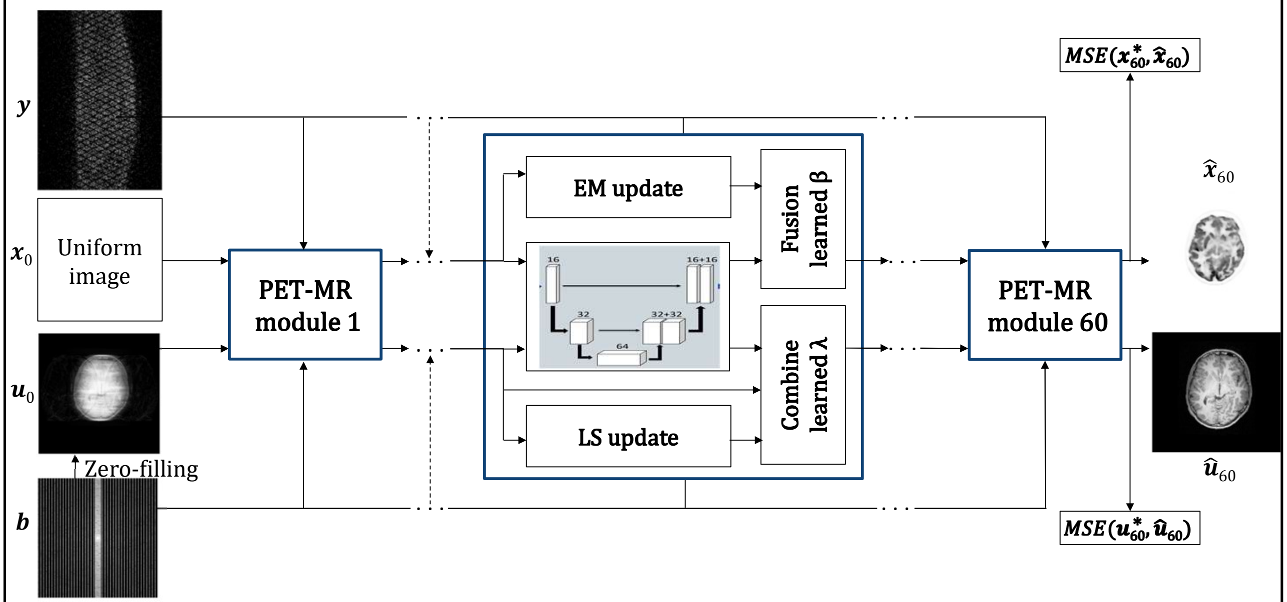
Joint DL PET-MR Reconstruction



Corda D'Incan, Schnabel and Reader, IEEE Medical Imaging Conference (Milan, Italy) 2022

40

Joint DL PET-MR Reconstruction



Corda D'Incan, Schnabel and Reader, IEEE Medical Imaging Conference (Milan, Italy) 2022

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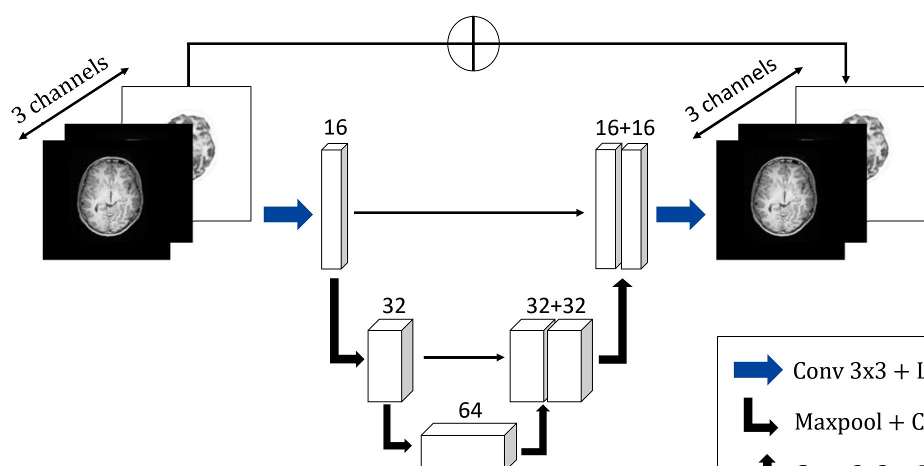
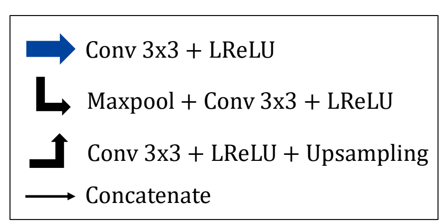
Joint regulariser architecture





- The network has ~58k parameters for **2D**
- The network has ~160k parameters for **3D**

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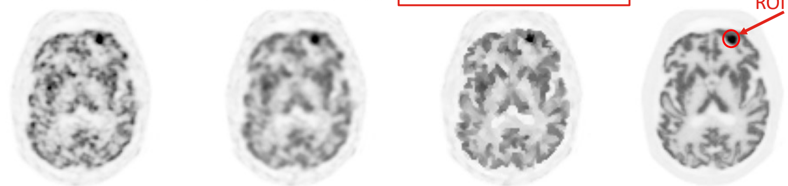
Joint reconstruction comparisons

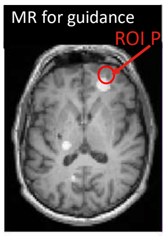
Decreasing global error

MR GUIDED

OSEM PSF	Q-MAPEM	B-MAPEM	PET target
NRMSE=74.4±0.8%	NRMSE=70.6±1%	NRMSE=66.5±0.7%	
NRMSE ROI=8.7±0.8%	NRMSE ROI=7.2±0.7%	NRMSE ROI=13.6±0.7%	

ROI P





Corda D'Incan, Schnabel and Reader, to be presented at the IEEE MIC 2022

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Joint reconstruction comparisons

Decreasing global error

MR GUIDED

OSEM PSF	Q-MAPEM	B-MAPEM	PET target
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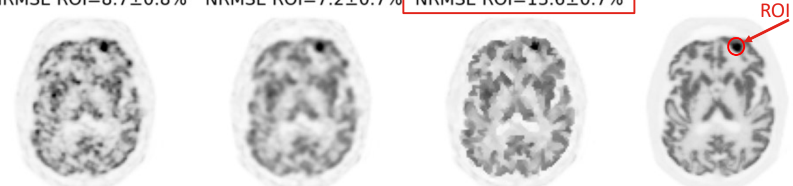
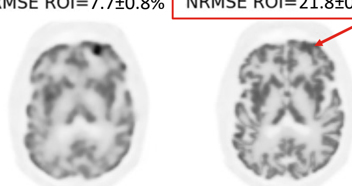
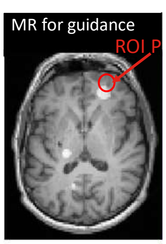
ROI P



Independent DL

Indep P	Indep P MR HD
NRMSE=60.1±0.6%	NRMSE=49.6±0.4%
NRMSE ROI=7.7±0.8%	NRMSE ROI=21.8±0.3%





Lower error

Corda D'Incan, Schnabel and Reader, to be presented at the IEEE MIC 2022

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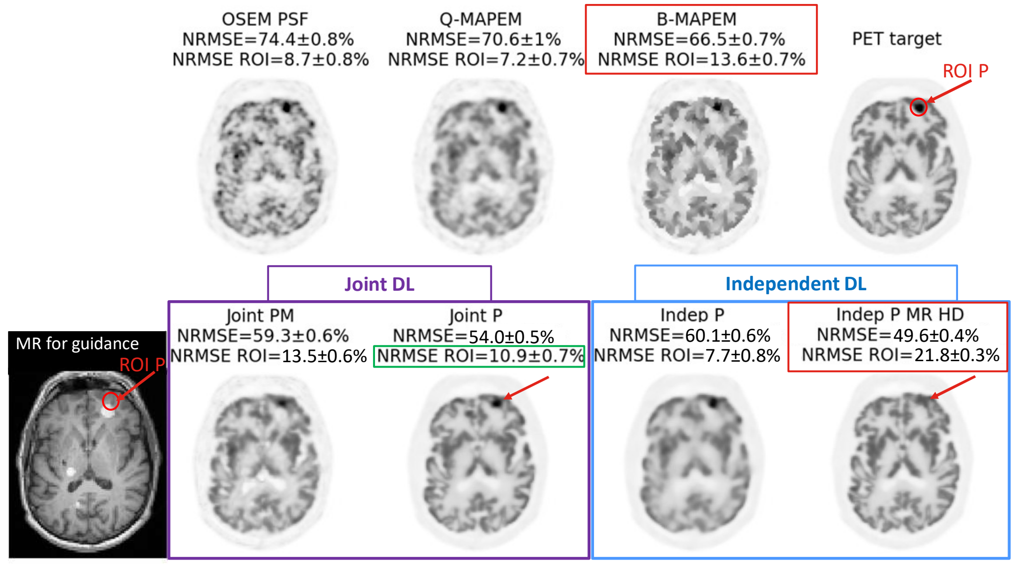
Joint reconstruction comparisons



Corda D'Incan, Schnabel and Reader, to be presented at the IEEE MIC 2022

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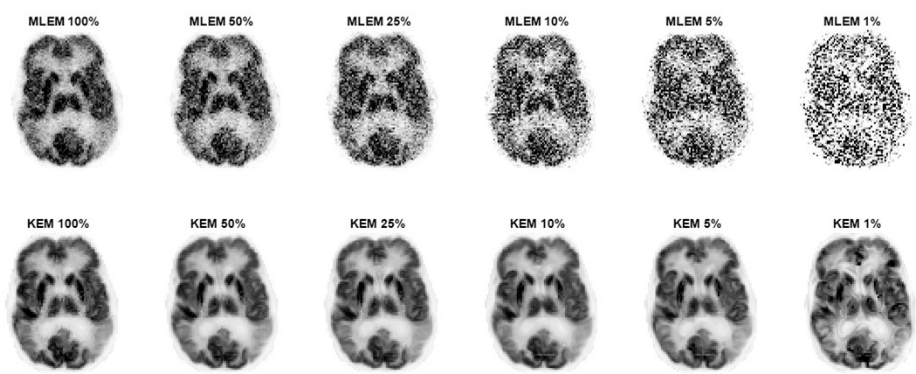
Kernel method for low dose [^{18}F]FDG (mMR)



Wang & Qi *IEEE TMI* 2015
Bland …., Reader *IEEE TRPMS* 2017

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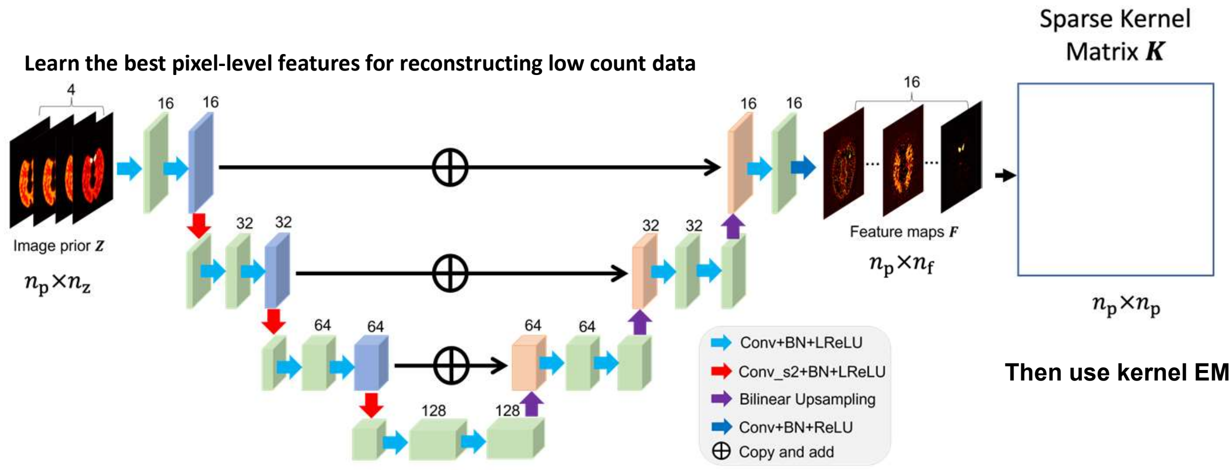
Deep kernel (Li & Wang 2022)



Figures courtesy Siqi Li & Guobao Wang

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Deep kernel: 2 second frames

(GE Discovery ST PET/CT in 2D mode, 20 mCi [^{18}F]FDG, cardiac scan)

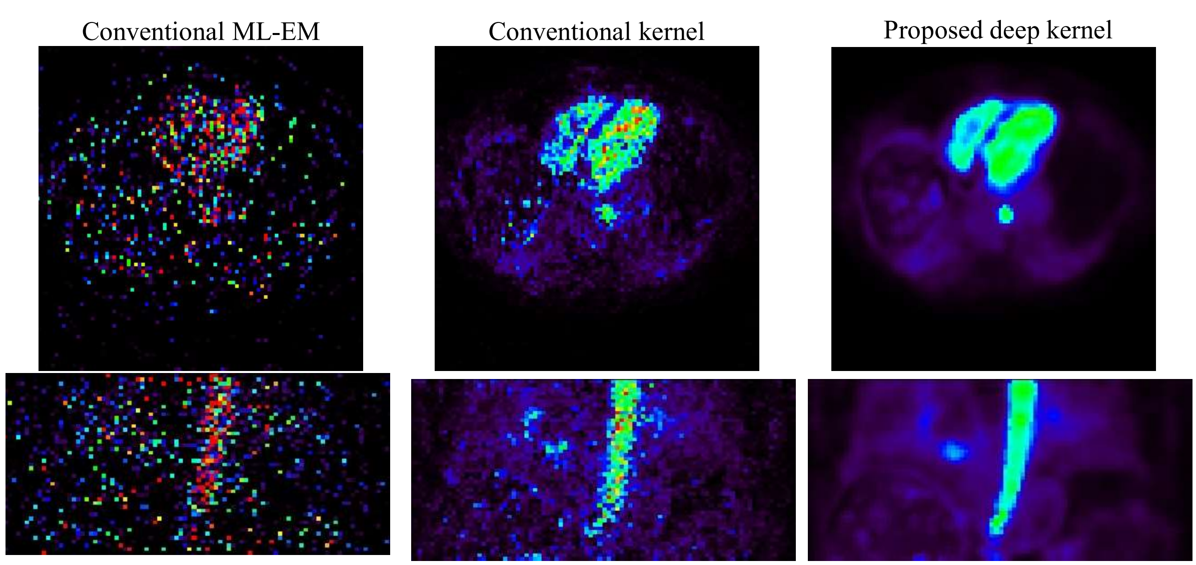

Figure courtesy Siqi Li & Guobao Wang

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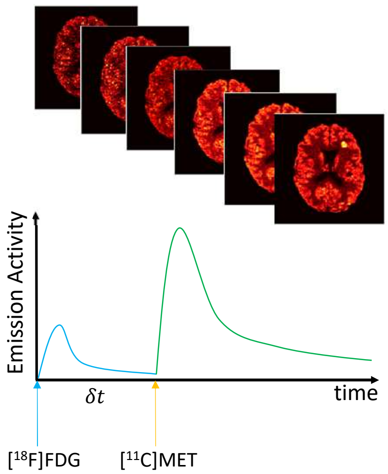
DL for Dual-Tracer [18F]FDG & [11C]MET Separation

Bolin, Marsden, Reader



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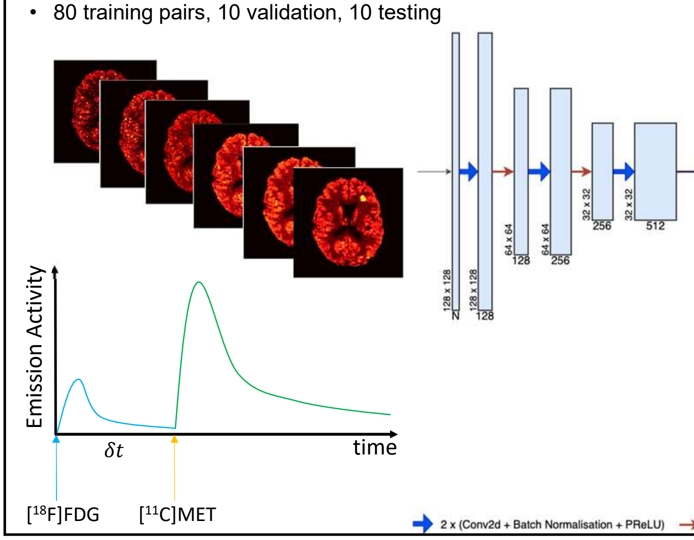
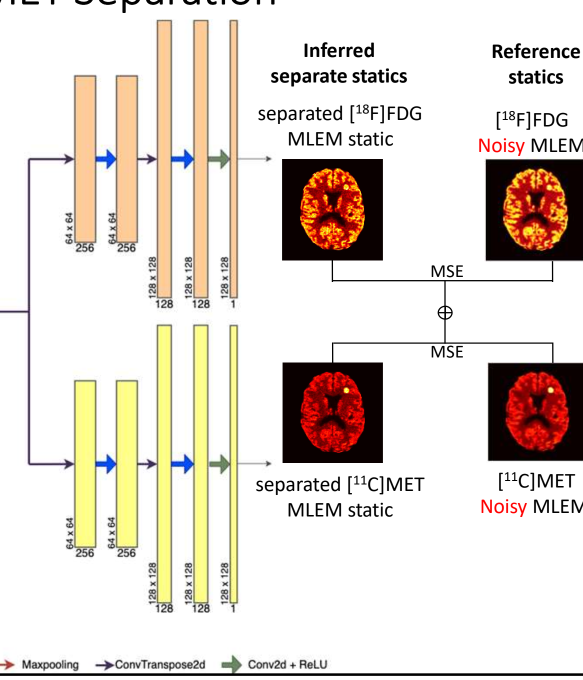
DL for Dual-Tracer [18F]FDG & [11C]MET Separation

Bolin, Marsden, Reader

- Input: dynamic noisy dual-tracer MLEM (δt = 0, 5, 10, 15 mins)
- Target: two static noisy single-tracer MLEM (δt = ∞)
- MSE loss, 800 epochs, mini-batch size = 4, learning rate: 5e-4
- 80 training pairs, 10 validation, 10 testing





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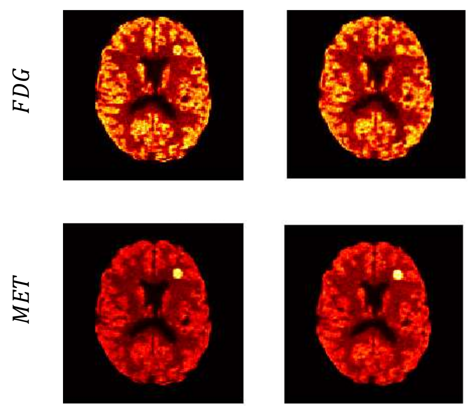
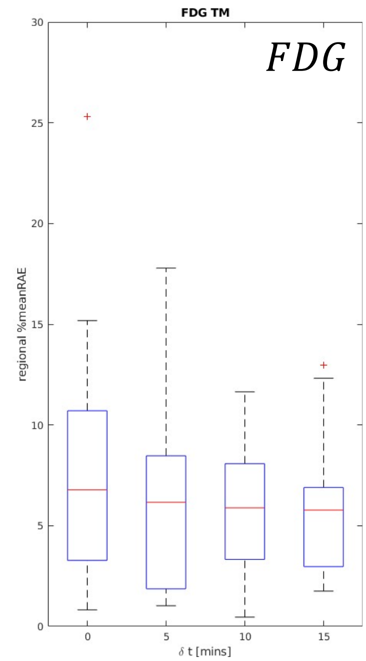
DL Separation for different δt

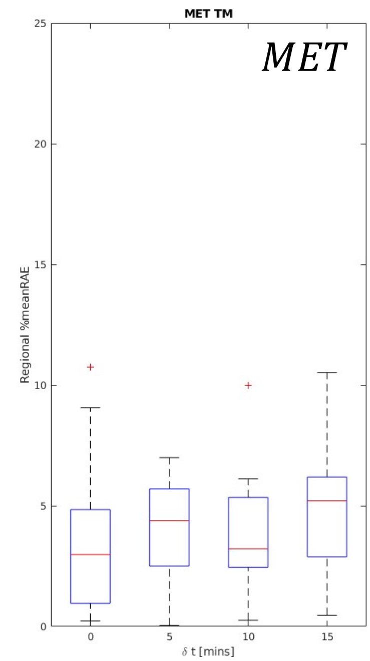
Bolin, Marsden, Reader

REFERENCE $\delta t = \infty$

INFERENCE $\delta t = 15\ min$







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Outlook

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Outlook

- Balance between two modelling extremes
  - Only use knowledge of maths, physics, biology, …
  - Only data
  - Inductive prior + data → model for inference
- Modular DL for robustness & validation of each component
  - DL module for 'inversion' of forward model, DL module for regularisation, DL for separation, …
- High quality references vs. self-supervision
- DL can improve image quality for a given count level
  - Or trade in for lower dose, and/or shorter scans
- Assess for clinical tasks, ideally with benchmark datasets (needed)
- Uncertainty quantification
- Better deep models with integrated multi-modal data

Generalisation (out of distribution)

Radon (1887-1956)

Data

Performance (within distribution)

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Thank you

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Deep Learning for PET Image Reconstruction

Andrew J. Reader, Guillaume Corda, Abolfazl Mehranian, Casper da Costa-Luis, *Student Member, IEEE*, Sam Ellis, and Julia A. Schnabel, *Senior Member, IEEE*

Journal of Nuclear Medicine October 2021, 62 (10) 1330-1333; DOI: https://doi.org/10.2967/jnumed.121.262303

HOT TOPICS

Artificial Intelligence for PET Image Reconstruction

Andrew J. Reader[1] and Georg Schramm[2]

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Department of Imaging and Path

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