AI and simulation in Medical Physics

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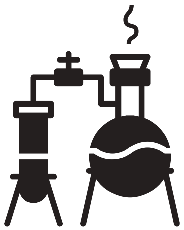
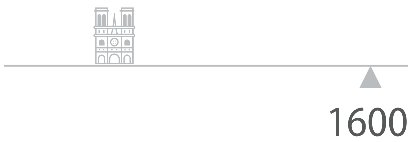
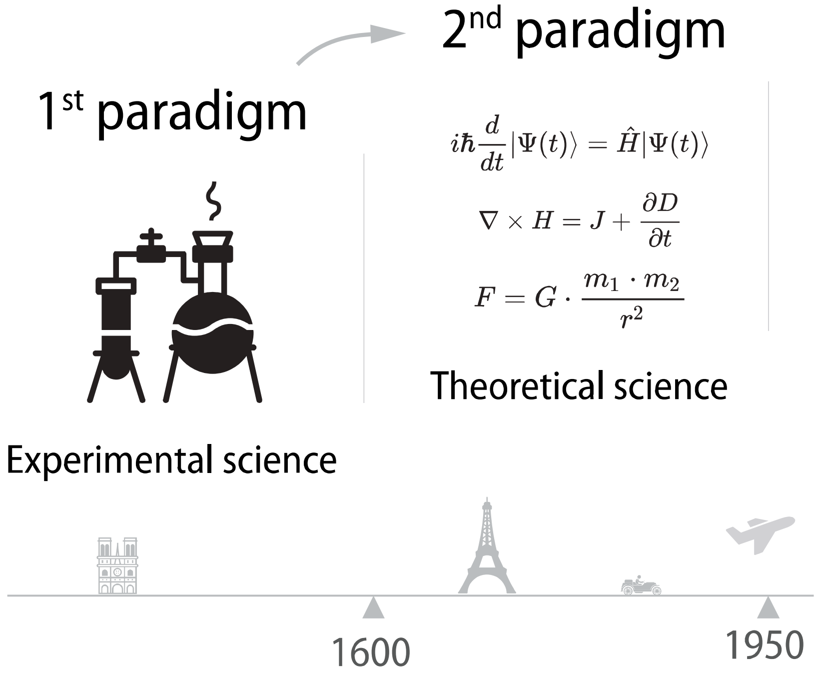
1st paradigm



Experimental science



[1] Jim Gray, 2007 [GRAY]



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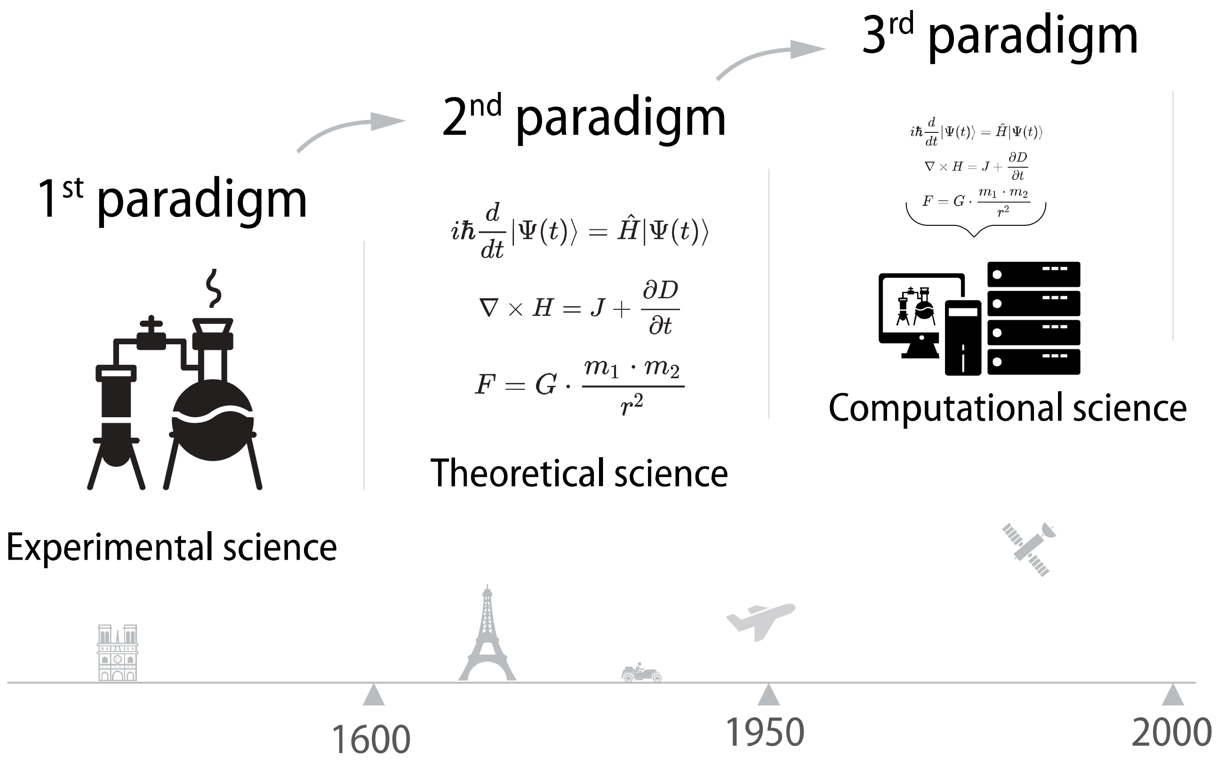

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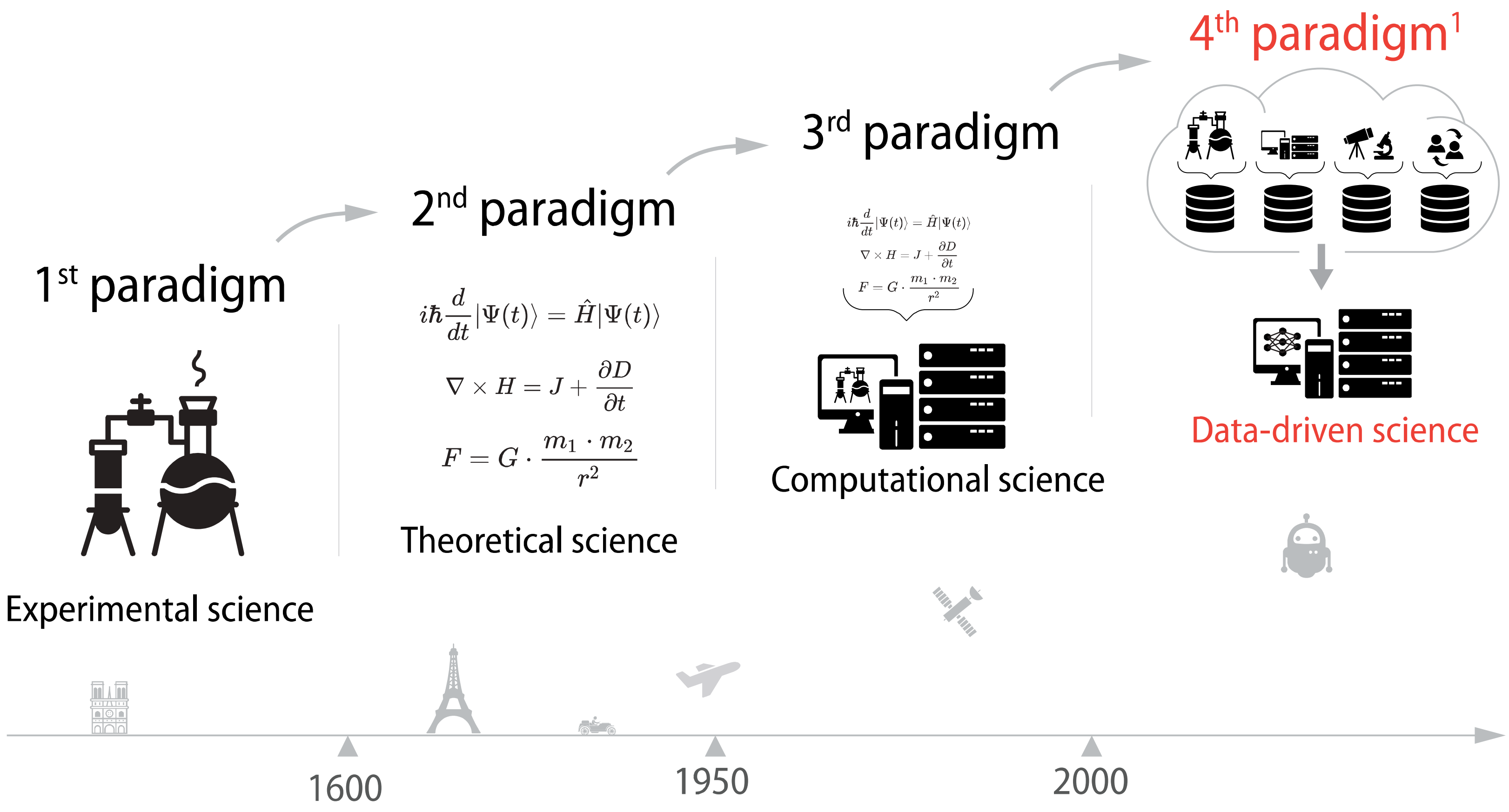

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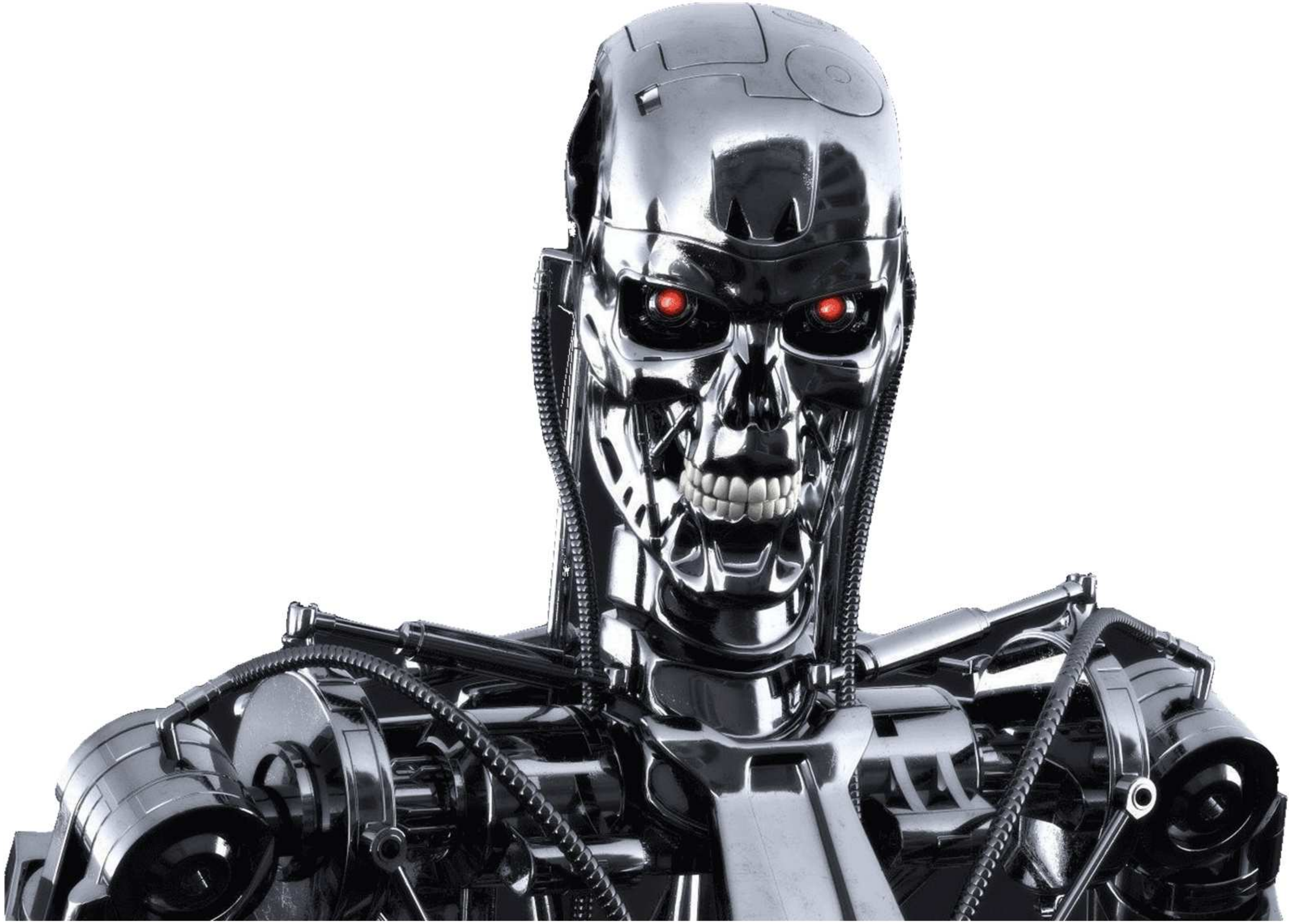


"With artificial intelligence we are summoning the demon" -- Elon Musk

Simon Leglaive 2020
https://sleglaive.pages.centralesupelec.fr/page/IA-MS-sept2020/slides/slides.html

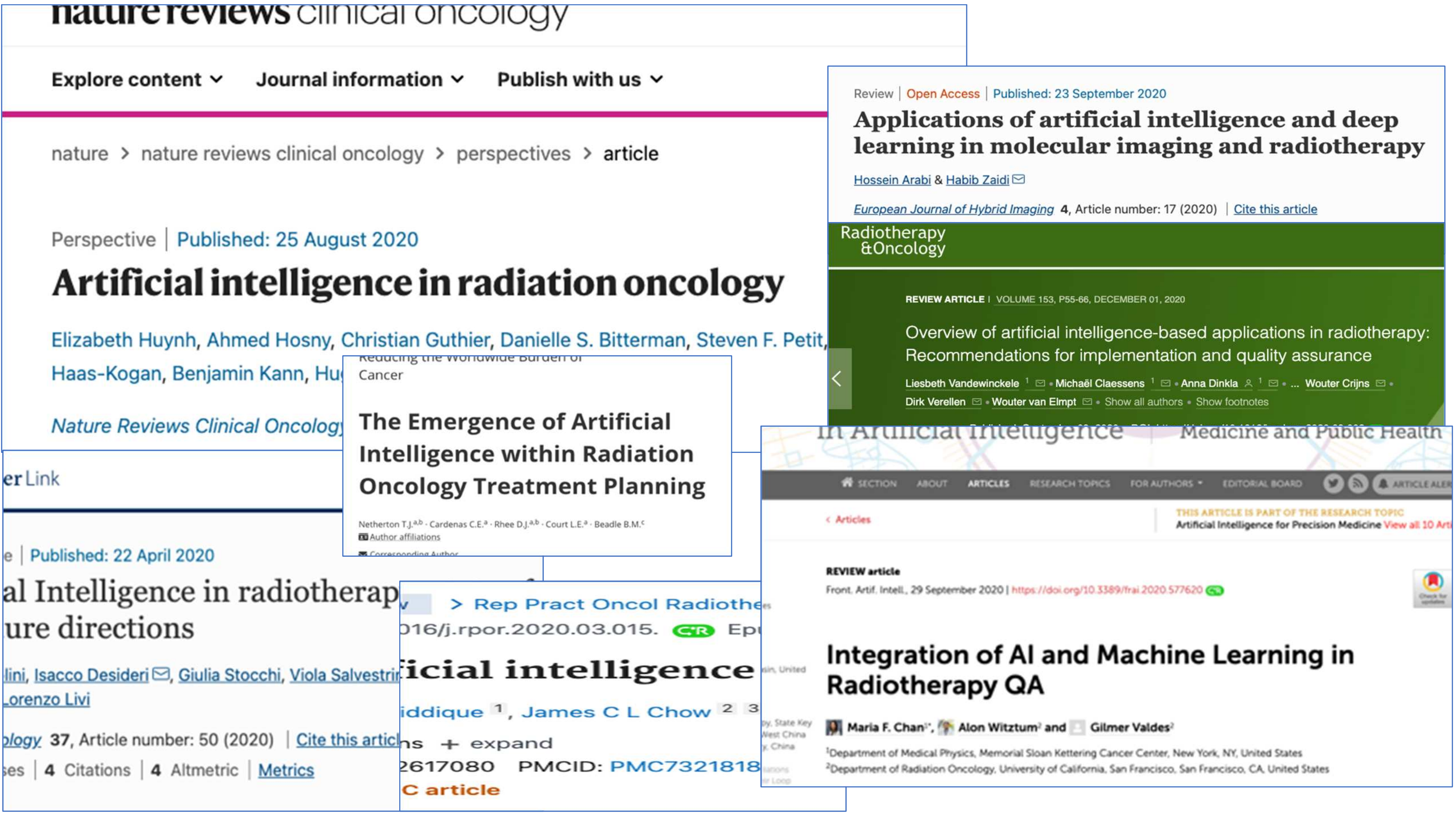
"We're really closer to a smart washing machine than Terminator"

-- Fei-Fei Li, Director of Stanford AI Lab

Outline

- **Part I : AI in medical physics**
- **Part II : AI for (Monte Carlo) simulation**
- **Conclusion**

[redacted]



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Haas-Kogan, Benjamin Kann,
Nature Reviews Clinical Oncolog
Review | Open Access | Published: 23 September 2020
Applications of artificial intelligence and deep learning in molecular imaging and radiotherapy
Hossein Arabi & Habib Zaidi
European Journal of Hybrid Imaging 4, Article number: 17 (2020) | Cite this article
Radiotherapy &Oncology
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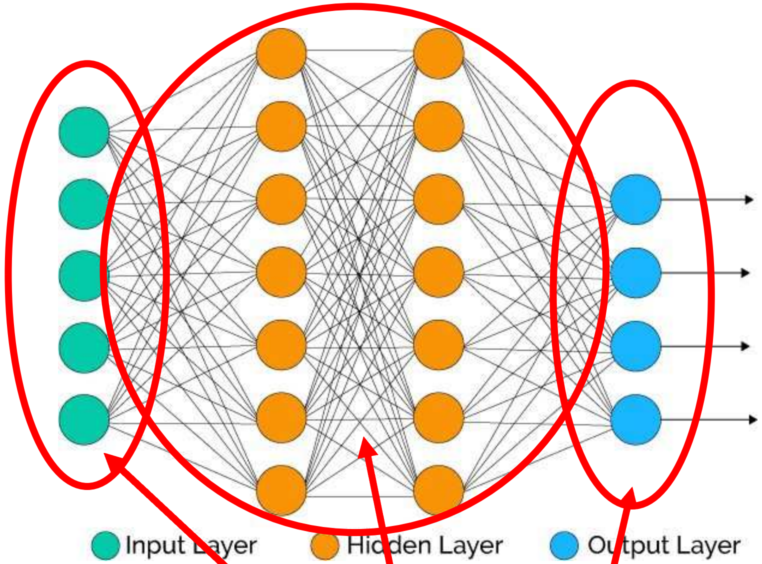
REVIEW article
Front. Artif. Intell., 29 September 2020 | https://doi.org/10.3389/frai.2020.577620
Integration of AI and Machine Learning in Radiotherapy QA
Maria F. Chan, Alon Witztum and Gilmer Valdes
Department of Medical Physics, Memorial Sloan Kettering Cancer Center, New York, NY, United States
Department of Radiation Oncology, University of California, San Francisco, San Francisco, CA, United States

Deep Learning (DL)

- **Step1**: learn a model (*training*)
  - Input = training database
  - Neural network architecture
  - Learning method (optimisation)

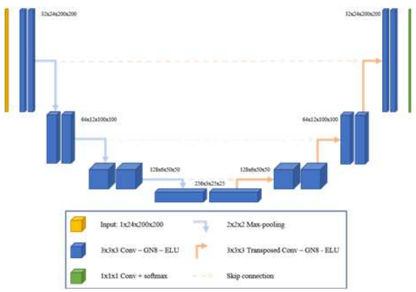
- **Step2**: use the model (*inference*)
  - New input data
  - Apply the NN model to get output

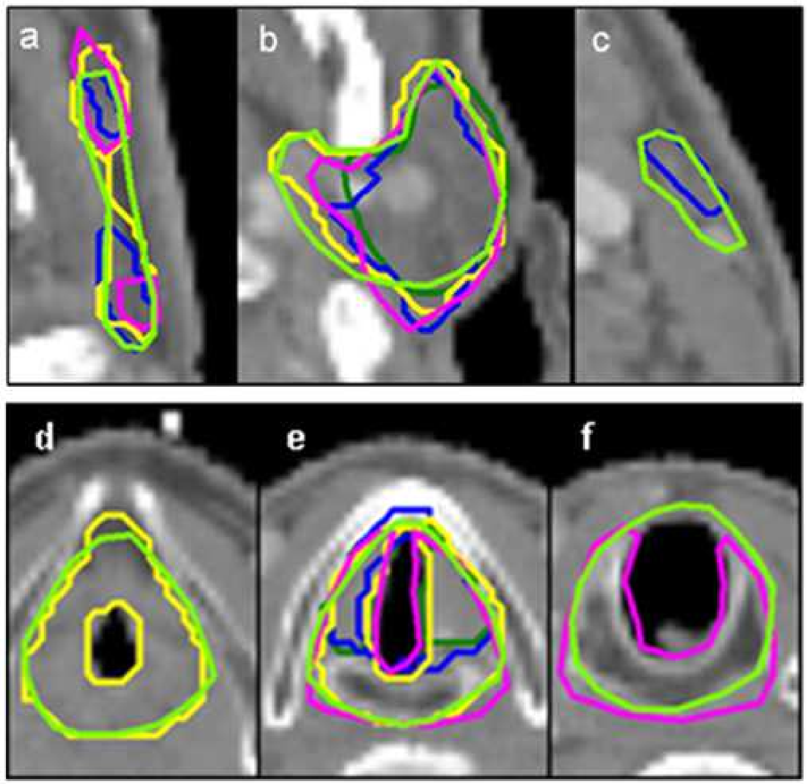


$$\underline{h}(x,\underline{\theta) =}\ \underline{y}$$

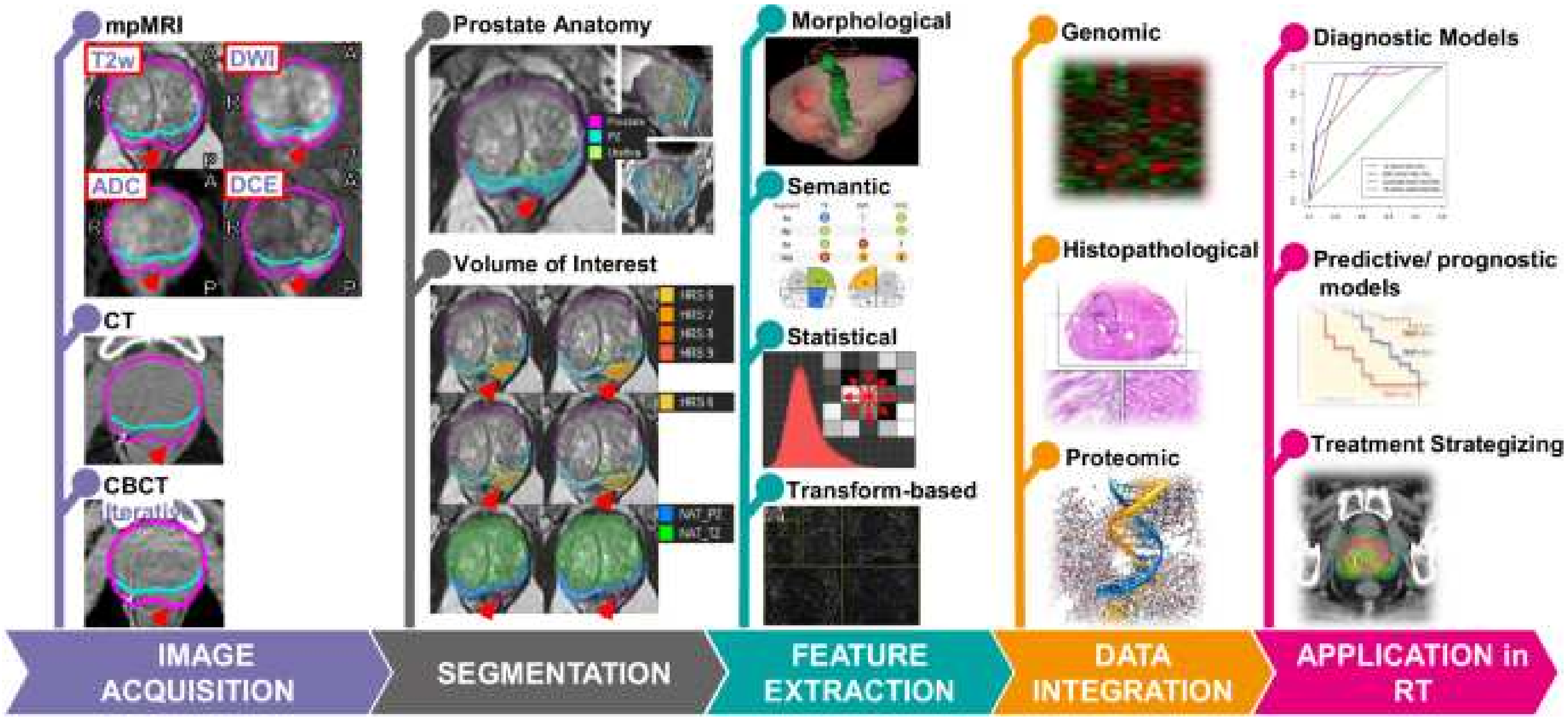
Segmentation with CNN

- Segmentation: one of the most tedius task, with high uncertainty
- For OAR, for lesions
- Automatic contouring with CNN
  - Input: an image (CT, MRI, etc)
  - Output: a mask (a binary image)





Prediction ("radiomics")



[Reuze2018]
[Arimura2018]

GAN: Generative Adversarial Network

- [Goodfellow et al 2014]
- Thousands of articles since

- Goal: learn a multidimensional distribution
- Generate "samples" from this distribution
- "Diffusion net" [Ho et al 2020] :
  - Dall-E, Midjourney, StableDiffusion
  - Text-to-image diffusion model

StyleGAN2

https://arxiv.org/abs/1912.04958

[Karras2019]

GAN: Generative Adversarial Network

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- “Diffusion net” [Ho et al 2020] :
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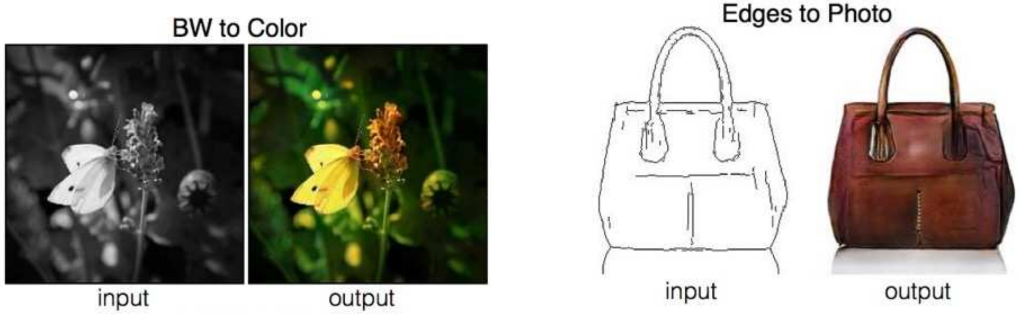
GAN - CGAN - LAPGAN - CatGAN - DCGAN - VAE-GAN - GRAN - S^2GAN - MGAN - BiGAN - GAN-CLS - ALI - CoGAN - f-GAN - Improved GAN - InfoGAN – SketchGAN
Context-RNN-GAN - EBGAN - IAN - iGAN - SeqGAN - SRGAN - VGAN - 3D-GAN - AC-GAN - AffGAN - GAWWN - b-GAN - C-RNN-GAN - CC-GAN - DTN - GMAN – IcGAN
LSGAN - MV-BiGAN - pix2pix - RenderGAN - SAD-GAN - SGAN - SSL-GAN - TGAN - Unrolled GAN - VGAN - AL-CGAN - MARTA-GAN - MDGAN - MPM-GAN - PPGN – PrGAN
SGAN - SimGAN - StackGAN - textGAN - AdaGAN - ID-CGAN - LAGAN - LS-GAN - SalGAN - Unim2im - ViGAN - WGAN - acGAN - ArtGAN - Bayesian GAN - BS-GAN - MalGAN
MaliGAN - McGAN - ST-GAN - WaterGAN - AEGAN - AM-GAN - AnoGAN - BEGAN - CS-GAN - CVAE-GAN - CycleGAN - DiscoGAN - GP-GAN - LR-GAN - MedGAN - MIX+GAN
RTT-GAN - SEGAN - SeGAN - SGAN - TAC-GAN - Triple-GAN - UNIT - DualGAN - FF-GAN - GoGAN - MAD-GAN - MAGAN - SL-GAN - Softmax GAN - TAN - TP-GAN – VariGAN
VAW-GAN - WGAN-GP - Î²-GAN - Bayesian GAN - CaloGAN - Conditional cycleGAN - CramÃ¨r GAN - DR-GAN - DRAGAN - ED//GAN - EGAN - Fisher GAN – Flow-GAN
GeneGAN - Geometric GAN - IRGAN - MMD-GAN - ORGAN - Pose-GAN - PSGAN - RankGAN - RPGAN - RWGAN - SBADA-GAN - SD-GAN - VEEGAN - WS-GAN - ARAE - BCGAN
CAN - Chekhov GAN - crVAE-GAN - DeliGAN - DistanceGAN - DSP-GAN - Dualing GAN - Fila-GAN - GANCS - GMM-GAN - IWGAN - PAN - Perceptual GAN – PixelGAN
RCGAN - RNN-WGAN - SegAN - TextureGAN - Î±-GAN - 3D-IWGAN - AE-GAN - AlignGAN - APE-GAN - ARDA - DAN - l-GAN - LD-GAN - LeGAN - MMGAN – MoCoGAN
ResGAN - SisGAN - ss-InfoGAN - SSGAN - SteinGAN - VRAL - 3D-RecGAN - ABC-GAN - ASDL-GAN - BGAN - CDcGAN - CGAN - constrast-GAN - Coulomb GAN – DM-GAN
GAN-sep - GAN-VFS - MGGAN - PGAN - SN-GAN - SS-GAN - VIGAN - ARIGAN - CausalGAN - D2GAN - ExposureGAN - ExprGAN - GAMN - GraspGAN - LDAN – LeakGAN
MD-GAN - MuseGAN - OptionGAN - PassGAN - RefineGAN - Splitting GAN - Î”-GAN - CM-GAN - GAN-ATV - GAP - GP-GAN - Progressive GAN - PSÂ²-GAN - SVSGAN – TGAN
3D-ED-GAN - ABC-GAN - ACtuAL - AttGAN - AttnGAN - BCGAN - BicycleGAN - CatGAN - CoAtt-GAN - ConceptGAN - Cover-GAN - D-GAN - DAGAN - DeblurGAN – DNA-GAN
DRPAN - FIGAN - FSEGAN - FTGAN - GANDI - GPU - HAN - HP-GAN - HR-DCGAN - IFcVAEGAN - In2I - Iterative-GAN - IVE-GAN - iVGAN - KBGAN - KGAN - LGAN – MLGAN
ORGAN - Pip-GAN - pix2pixHD - Sobolev GAN - StarGAN - TGAN - tripletGAN - VA-GAN - XGAN - ZipNet-GAN - ACGAN - CA-GAN - ComboGAN – DF-GAN
Dynamics-Transfer GAN - EnergyWGAN - ExGAN - f-CLSWGAN - FusionGAN - G2-GAN - GAGAN - GAN-RS - GANG - GANosaic - IdCycleGAN - manifold-WGAN – MC-GAN
MIL-GAN - MS-GAN - PacGAN - PN-GAN - PPAN - RAN - SGAN - SRPGAN - ST-CGAN - Super-FAN - TV-GAN - UGACH - UV-GAN - VGAN - weGAN - AdvGAN - CFG-GAN
CipherGAN - Cross-GAN - dp-GAN - ecGAN - FusedGAN - GeoGAN - GLCA-GAN - LAC-GAN - MaskGAN - SG-GAN - SketchyGAN - tempoGAN - UGAN – AmbientGAN
ATA-GAN - C-GAN - CapsuleGAN - DA-GAN - DP-GAN - DPGAN - First Order GAN - GC-GAN - LB-GAN - MAGAN - ND-GAN - PGD-GAN - RadialGAN - SAR-GAN – SCH-GAN
StainGAN - SWGAN - VoiceGAN - WaveGAN - Attention-GAN - B-DCGAN - BAGAN - BranchGAN - D2IA-GAN - DBLRGAN - E-GAN - ELEGANT - Fictitious GAN – GAAN
GONet - memoryGAN - MTGAN - NCE-GAN - NetGAN - OCAN - OT-GAN - PGGAN - Sdf-GAN - Social GAN - Spike-GAN - ST-GAN - Text2Shape - tiny-GAN – VOS-GAN
3D-PhysNet - AF-DCGAN - BEAM - CorrGAN - D-WCGAN - Defo-Net - DSH-GAN - DTR-GAN - DVGAN - EAR - FBGAN - FusionGAN - Graphical-GAN - IterGAN – M-AAE
MelanoGAN - MGGAN - ModularGAN - NAN - PM-GAN - ProGanSR - PS-GAN - ReConNN - SAGA - sGAN - Sketcher-Refiner GAN - SyncGAN - TGANs-C – UT-SCA-GAN
AdvEntuRe - AVID - BourGAN - BRE - cd-GAN - cowboy - CSG - Defense-GAN - DialogWAE - DTLC-GAN - FairGAN - Fairness GAN - FakeGAN - FBGAN - FC-GAN - GAF - GAN
Q-learning - GAN-SD - GAN-Word2Vec - GANAX - GT-GAN - HAN - HiGAN - hredGAN - MC-GAN - MEGAN - MolGAN - N2RPP - PD-WGAN - POGAN - PSGAN – ReGAN
RegCGAN - RoCGAN - SAGAN - SG-GAN - speech-driven animation GAN - WGAN-CLS - Adaptive GAN - APD - BinGAN - BWGAN - CapsGAN - CR-GAN - DMGAN – EL-GAN
FrankenGAN - GAIN - GANG - GATS - IR2VI - IRGAN - JointGAN - JR-GAN - LCC-GAN - MedGAN - MMC-GAN - Modified GAN-CLS - PP-GAN - SeUDA – SN-DCGAN
SN-PatchGAN - SoPhie - SR-CNN-VAE-GAN - StarGAN-VC - table-GAN - tcGAN - TD-GAN - tempCycleGAN - VAC+GAN - acGAN - AlphaGAN - AMC-GAN - CE-GAN - ciGAN
CT-GAN - DE-GAN - Dropout-GAN - Editable GAN - FGGAN - GAIA - GAP - IntroVAE - ISGAN - LBT - Lipizzaner - MIXGAN - PIONEER - RaGAN - Resembled GAN – sAOG
Sem-GAN - SGAN - SiGAN - TequilaGAN - WGAN-L1 - BEGAN-CS - Bellman GAN - BridgeGAN - DOPING - GIN - GM-GAN - ISP-GPM - MinLGAN - Recycle-GAN - ScarGAN
Skip-Thought GAN - StepGAN - T2Net - TreeGAN - X-GANs - AE-OT - AIM - Bi-GAN - BubGAN - CinCGAN - ClusterGAN - DADA - DeepFD - ESRGAN - GAN Lab – GAN-AD
GANVO - GcGAN - GraphSGAN - IGMM-GAN - MeRGAN - SAM - SiftingGAN - SLSR - Twin-GAN - WaveletGLCA-GAN ...

Main GAN approaches

- Pix2Pix [Isola2017]

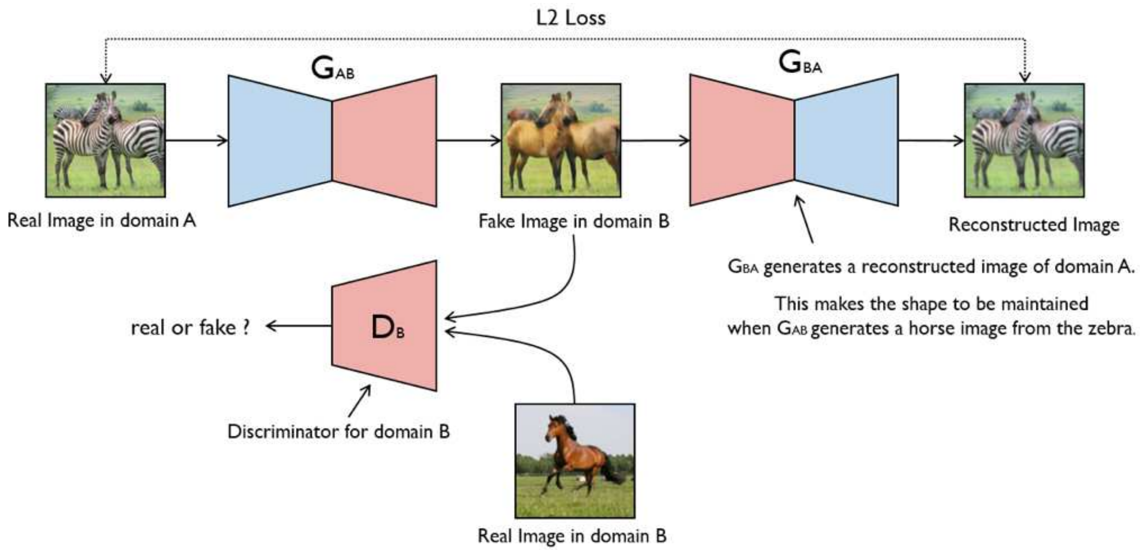
  Conditional GAN



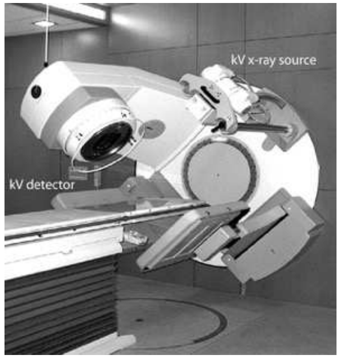
- CycleGAN [Zhu2017]

  Pair of Cycle consistant GANs

  No need for paired training data

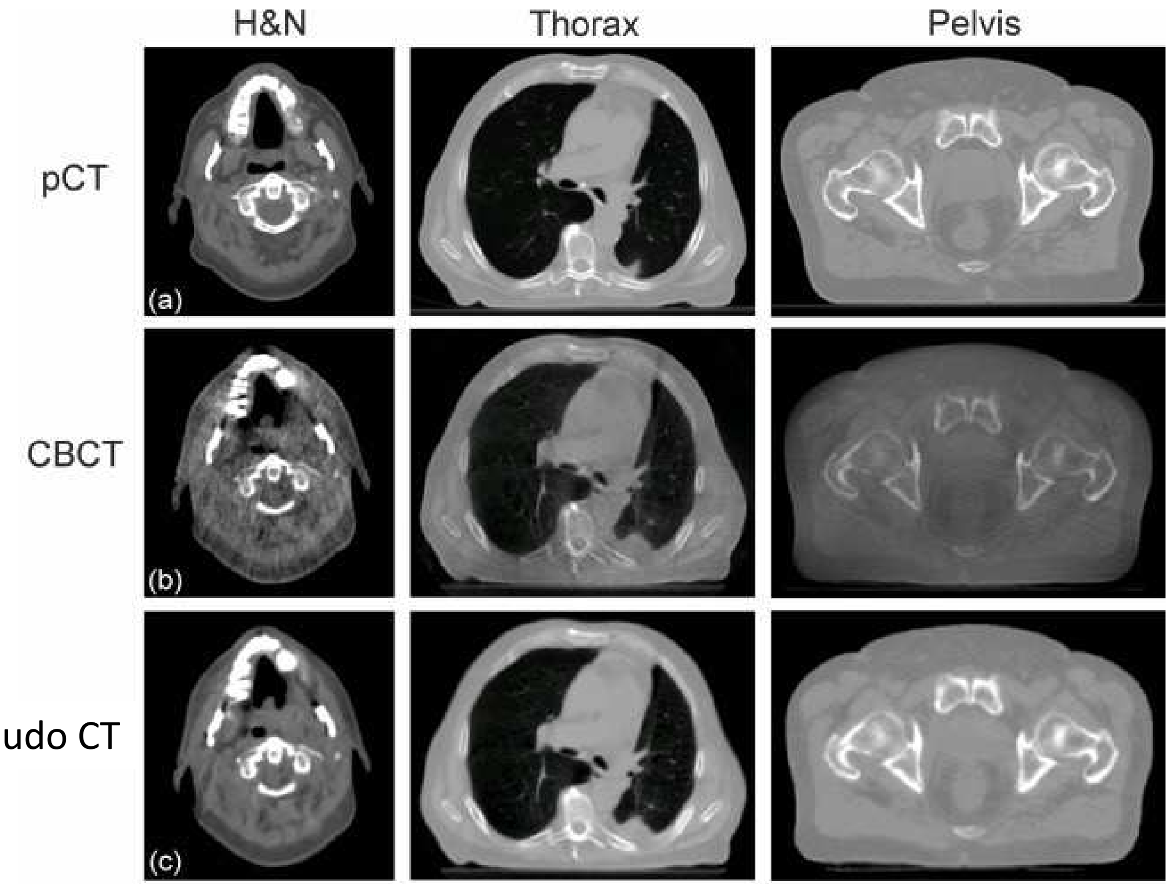


GAN for pseudoCT from CBCT



[Liang2019], [Kinda2020]

CycleGAN



GAN for pseudoCT from MRI

- In radiation therapy, for dose computation
- Lot of litteratures, e.g. [Robert 2020 HDR]

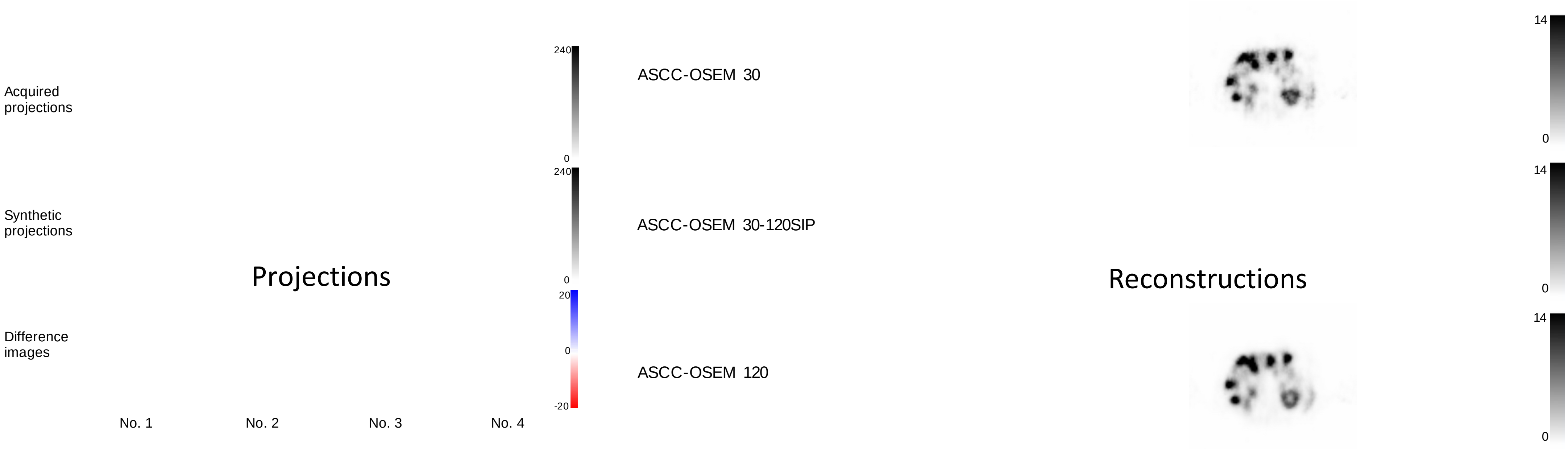
GAN for attenuation map in PET or SPECT

[Dong2019] [Yang2019] [Shiri2019]

- cycleGAN
- To create a “attenuation map” to be included in the reconstruction

GAN for intermediate SPECT projection

- Long 3D SPECT acquisition with rotation gantry, around 120 angles
- [Rydén2020] Synthetic intermediate projections (SIPs)
- SIPs to be used during the reconstruction



Conclusion Part1

AI in **Medical Physics** : already there !

- Large success in auto segmentation (still work todo)
- Concept: deep-based radiomics (data based biomarkers)
- Concept: image generation (pseudoCT, etc)
- Many others applications

It is a “new” hammer, if you have nails, it is good.

[redacted]

Outline

- **Part I : AI in medical physics**
- **Part II : AI for (Monte Carlo) simulation**
- **Conclusion**

DL could it be useful for MC ?

- Already experimented in several publications
- Especially in HEP and MedPhys

[Sarrut et al Frontiers 2021]

TABLE 1 | AI-based applications related to Monte Carlo simulations and their corresponding input data type. The word "particles" as input type refers to a vector of particle properties such as energy, position, direction, weight, etc. CNN stands for convolutional neural networks and MLP stands for multi-layer perceptron.

Application	Input type	Refs (among others)	Main ML types
Dose computation	image	[49, 63, 79, 85, 90, 104, 116, 117, 147]	CNN, U-net
Dose denoising	image	[43, 59, 71, 101, 103, 111, 131, 153][1]	CNN, U-net
SPECT scan-time reduction	image	[82, 119, 121]	CNN, U-net
CBCT scatter modelling	image	[27, 58, 60, 75, 79, 84, 87, 88, 140, 145, 152, 155]	CNN, U-net
PET attenuation/scatter correction	image	[6, 97]	CNN, U-net
Detector response modelling	particles	[126, 144]	GAN, MLP
Source + phase space modelling	particles	[108, 125, 127]	GAN
Event selection	particles	[8, 12, 40, 46, 93, 98, 100, 102, 107, 157][2]	MLP, CNN
Interaction position in scintillators	various	[23, 33, 37, 99, 109, 110, 122, 150, 154]	MLP, CNN

[1] *http://hdl.handle.net/11603/19255*
[2] *http://hdl.handle.net/2078.1/thesis:14550*

Frontiers in Physics | www.frontiersin.org 3 October 2021 | Volume 9 | Article 738112

Dose computation/planning with AI

- Task1: fast dose computation/prediction
  - Input: CT + contour + MLC fluence map
  - Output: dose distribution

- Task2: planning optimization
  - Input: CT, planning constraints/objectives, fast dose algo
  - Output: beam configurations and parameters

Nguyen, D. et al. A feasibility study for predicting optimal radiation therapy dose distributions of prostate cancer patients from patient anatomy using deep learning. *Sci. Rep.* **9**, 1076 (2019).

Campbell, W. G. et al. Neural network dose models for knowledge-based planning in pancreatic SBRT. *Med. Phys.* **44**, 6148–6158 (2017).

Example: EBRT

- DeepDose [Kontaxis2020]
- Input:
  - Patient anatomy CT + contours
  - IMRT MLC shape or segment
- Output: dose distribution
- Training database 100 patients, prostate 5-beams IMRT, ~4k segments, dose from segment with MC, normalized 100 MU
- 3D U-Net
- Compared to MC ; 1 min patient in total
- For online replanning

Radiopharmaceutical therapy

DeepDose [Lee2019] … same name [Tsekas2021]

DL-based Monte Carlo denoising

- Post-processing, CNN-based denoising
- Training dataset: pairs of high-noise/low-noise dose distributions
- Photon, proton dose
- 10–100 times fewer particles
- Dose gradients preserving ? Memory ?

[Javaid2021]

[Fornander2019]
[Neph2019]
[Peng2019]
[Javaid2019]
[Kontaxis2020]
[Javaid2021]
[Bai2021]

WARNING : need for objective task-based evaluation of DL denoising !

DL-based scatter estimation

[Lalonde2020]
[Lee2019]
[Maier2019]
[van der Heyden2020]

- DL trained from CBCT projections simulated with MC
- Generate estimated scatter images from projections
- e.g. Heyden2020: "*Monte Carlo Based Scatter Removal Method for Non-isocentric Cone-Beam CT Acquisitions Using a Deep Convolutional Autoencoder*"

Replace the Monte Carlo simulation

[van den Heyden2020]

[redacted]

Learning a Linac phase-space

Radiation Therapy Linac head simulation

e- beam

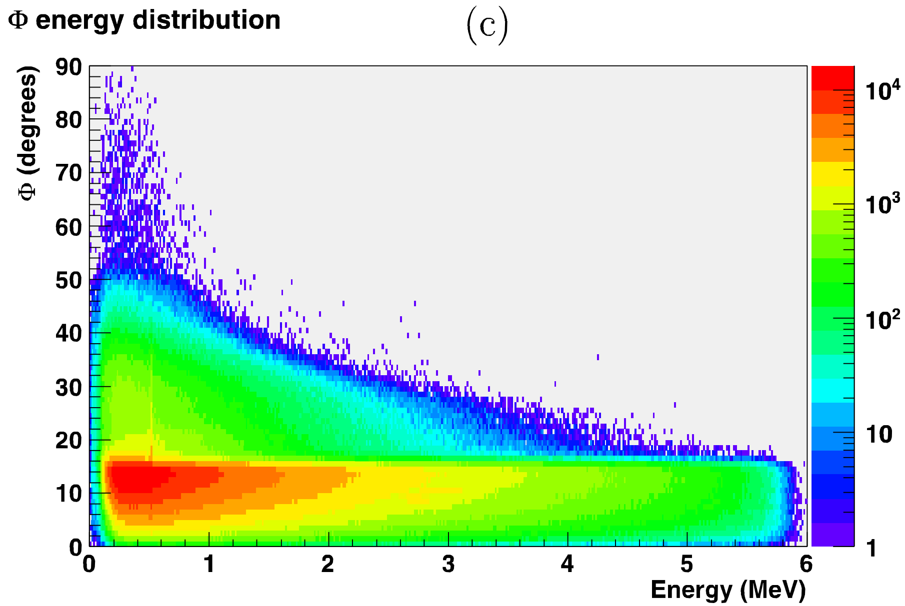
Phase space plane

Few photons exiting
VRT (brem splitting)

Goal: determine beam characteristics
(energy, position, direction distributions)

Phase Space (PHSP)

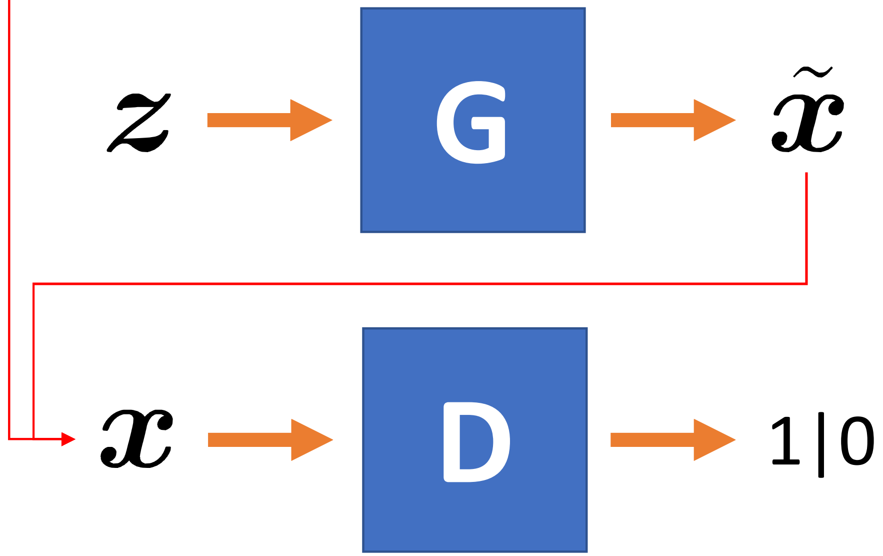
- Store beam properties as **Phase Space**
  - A PHSP is a list of particles (around 10^8, 10^9)
  - Properties: E, x, y, z, dx, dy, dz, w, (time)
- Advantages:
  - Computed only once
  - Fast to use
  - Can be shared
- Drawback
  - Several GB
  - When a cluster is used, should be shared among workers
  - Limited number of particles
- Need for an analytical model



Example of dependence of direction ϕ and energy

GAN: Generative Adversarial Network

- Training dataset $\boldsymbol{x} \in \mathbb{R}^d$
  - Dimension d=7 (E, X, Y, Z, dX, dY, dZ)
  - Samples of unknown p_{real}
- Generator $G(\boldsymbol{z}; \boldsymbol{\theta}_G)$
- Discriminator $D(\boldsymbol{x}; \boldsymbol{\theta}_D)$



Loss function

- GAN notoriously difficult to train
- Alternative formulations: **Wasserstein GAN** [Arjovsky 2017]

- “Earth-mover” distance (EMD) : cost of the optimal transport
- Un-tracktable in practice, but approximated:

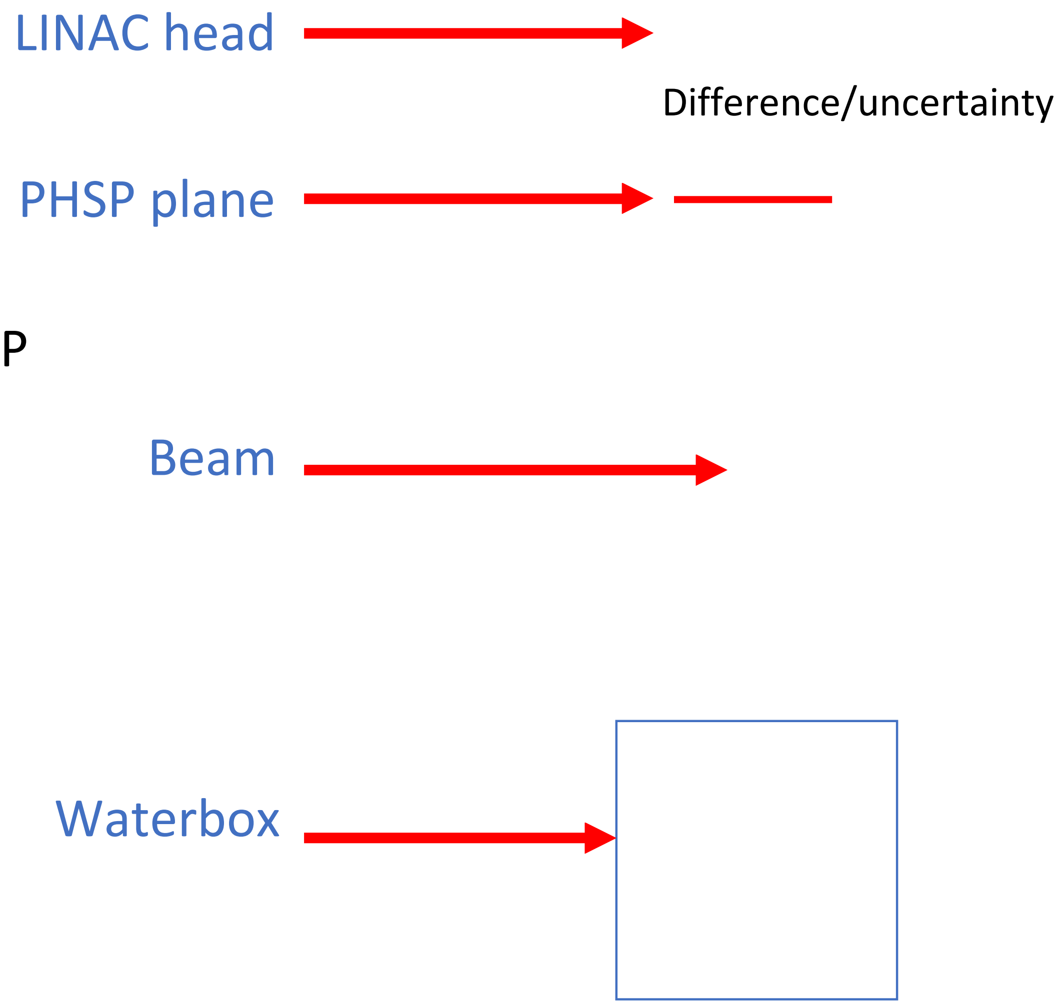
$$
\begin{aligned}
J_D\left(\boldsymbol{\theta}_D, \boldsymbol{\theta}_G\right) &= \mathbb{E}_{\boldsymbol{z}}\left[D(G(\boldsymbol{z}))\right] - \mathbb{E}_{\boldsymbol{x}}\left[D(\boldsymbol{x})\right] \\
J_G\left(\boldsymbol{\theta}_D, \boldsymbol{\theta}_G\right) &= -\,\mathbb{E}_{\boldsymbol{z}}[D(G(\boldsymbol{z}))]
\end{aligned}
$$

Experiments

PHSP from IAEA web site

PHSP	Size	Nb of particles
Elekta PRECISE 6MV	2 files of 3.9 GB	1.3×10^8 photons each file
CyberKnife IRIS 60mm	2 files of 1.6 GB	5.8×10^7 photons each file

Results



- Dose distribution in water from PHSP
  10^8 primary photons

- Compare dose between:
  1. PHSP1 vs PHSP2
  2. PHSP1 vs GAN

- Voxel by voxel dose comparison

Results

Distributions of relative differences between

- PHSP1 and PHSP2
- PHSP1 and GAN

- **Sufficient for dose but not perfect**
- **Smooth-out 511 keV peak**

Vertical lines indicate the mean differences

Difference relative to the prescribed dose

Learning phase-space for SPECT simulation

SPECT simulation

- Part1: from emission to patient exiting gamma
- Part2: track gamma inside the detector

Training dataset

Train a GAN to produce exiting gamma from a given source

- Step1: run low stats MC, consider exiting gammas
- Step2: train a GAN
- Step3: use GAN a source

Conditional GAN

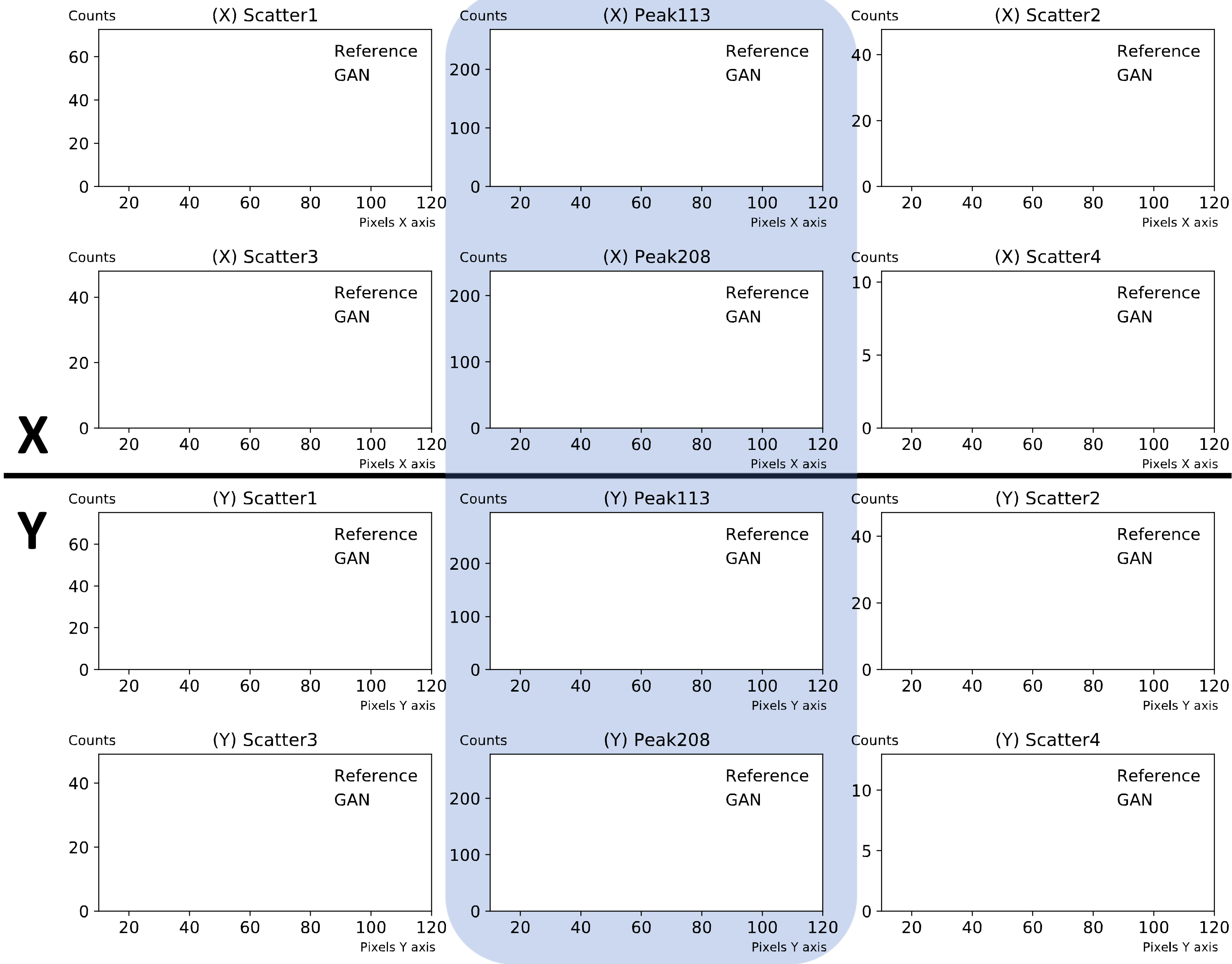
Train with one given **phantom** (CT, patient) …

… but with **homogeneous** activity

Conditional input activity map.

[Saporta et al, PMB 2022]

Results



2D projections
Lu177 (1 peak & scatter)

Conditional GAN

- Still need a training for each phantom
- But generic to any activity distribution

[Saporta et al, PMB 2022]

Combine GAN and ANN

PET GAN

Back-to-back GAN photon source for PET Monte Carlo simulation

[Sarrut et al, PMB 2023 - submitted]

[PMB 2018]

[PMB 2019]

[PMB 2022]

[PMB 2021]

[redacted]

GATE 10 (beta)

- New version coming soon
- Macros script replaced by Python scripts

    pip install opengate

- Multi-thread
- integration
- +90 tests and examples

Open and Open-source

https://github.com/OpenGate/opengate

Next GATE scientific meeting

- Cracow, Poland
- Organized by Wojciech Krzemien
- **24 April** : hackathon
- **25 to 26 April 2023**

Conclusion

- **AI** and **MC** can be combined in various ways
- **GAN** to produce distributions (image, particles)
- “New” toolbox, **data-driven** (crap-in, crap-out)
- **Open** science, available toolkits

- Limitations
  - Training dataset size and quality (curation)
  - Unclear modeling of “rare” events (e.g. 511 keV peak)
  - Evaluation may be “optimistic”

- Perspectives
  - AI is a numerical method, not magic
  - Data is gold
  - Summer is coming

Lyon, France

Thanks for your attention !