Deep Learning in Monte-Carlo simulations

GAGA: GAN for GATE

David Sarrut, Nils Krah, Jean-Michel Létang

University of Lyon

CREATIS, CNRS UMR5220, Inserm U1044, INSA-Lyon, Université Lyon 1, France

CREATIS Research Lab

CREATIS

www.creatis.insa-lyon.fr

- CREATIS : 200 persons, 70 perm, 6 teams
- Research group :
  - 3 permanents researchers
  - 4 PhD students
  - 4 post-doc
- Two main themes:
  - Image reconstruction, IGRT, registration
  - Simulations (Monte-Carlo)

UNIVERSITÉ DE LYON

cnrs dépasser les frontières

Léon Bérard cancer center (CLB)

- Private-public structure
- One over 20 centers in France
- Dedicated to fight cancer

CENTRE DE LUTTE CONTRE LE CANCER LEON BERARD

www.centreleonberard.fr

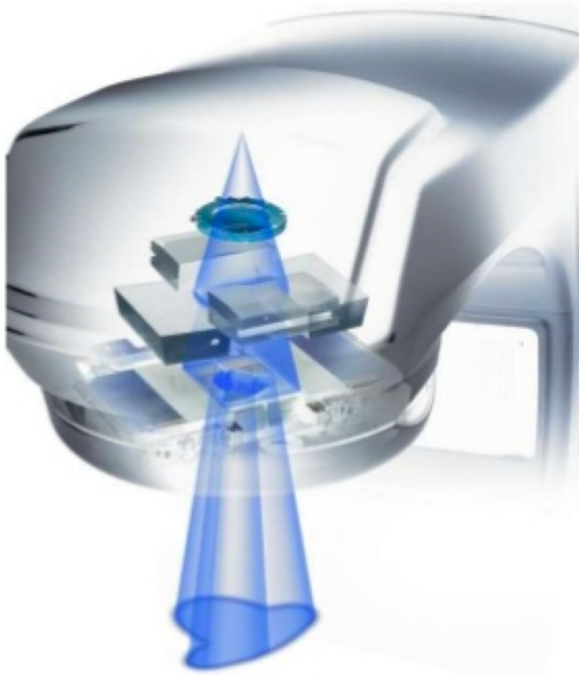
- **Radiation therapy** department
- **Nuclear medicine** department

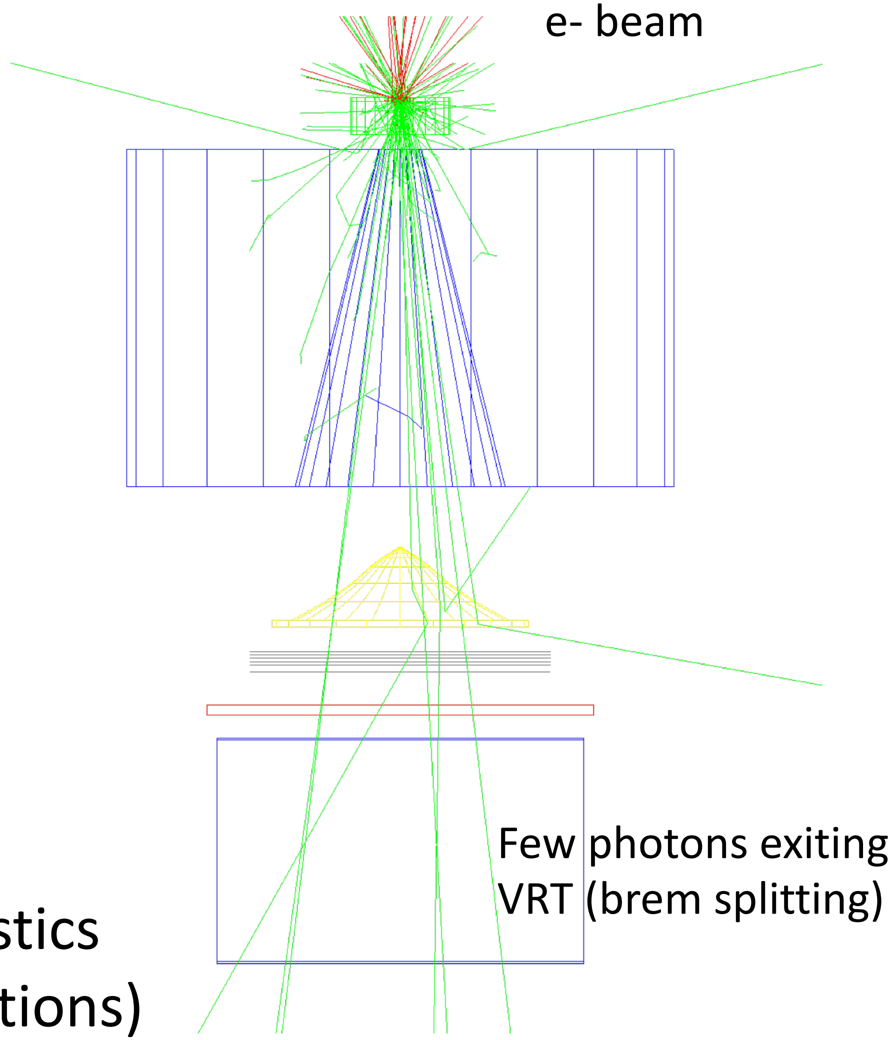
- Strong link with clinical staff, access to data
- Lyrican project

LyriCAN

LYon Recherche Innovation contre le CANcer

Radiation Therapy Linac head simulation





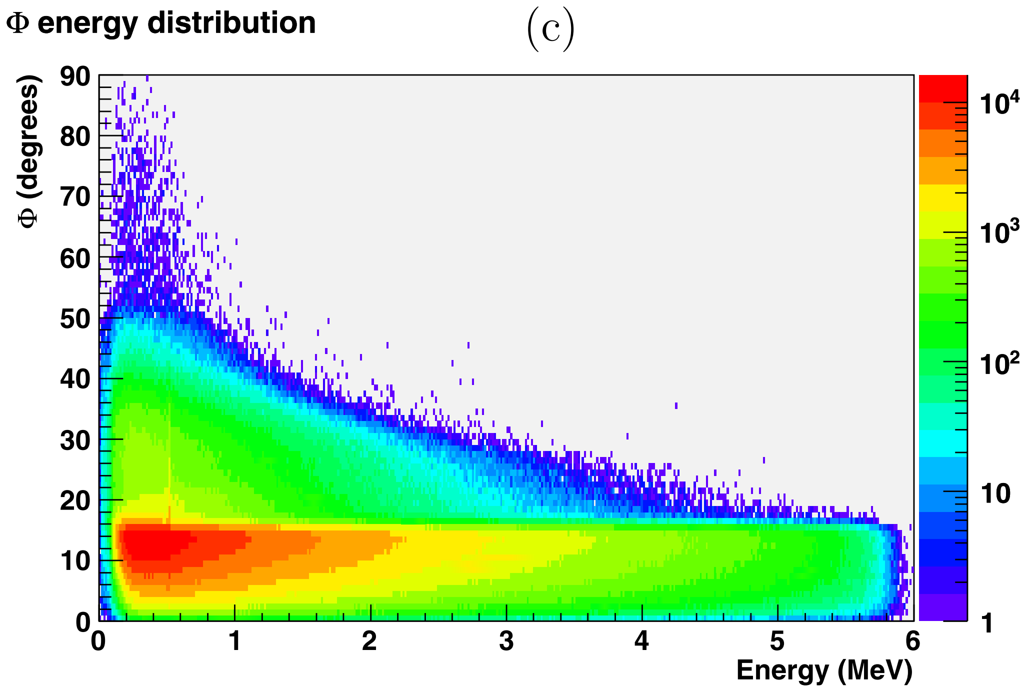
Goal: determine beam characteristics
(energy, position, direction distributions)

Phase Space (PHSP)

- Store beam properties as **Phase Space**
  - A PHSP is a list of particles (around 1e8, 1e9)
  - Properties: E, x, y, z, dx, dy, dz, w

- 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
  - Extensive description, not a model
  - Latent variance [Sempau2001]



Example of dependence of direction ϕ and energy.

Virtual Source Models

- Several VSM have been proposed
  - [Fix2001] [Grevillot2011] [Chabert2016], …
  - Histograms-based description (6D !): correlations bw variables
  - Analytical function model, adapted sampling procedures
  - Correlated-histograms with adaptive binning schemes, Kernel-Density Estimator (KDE)

  …

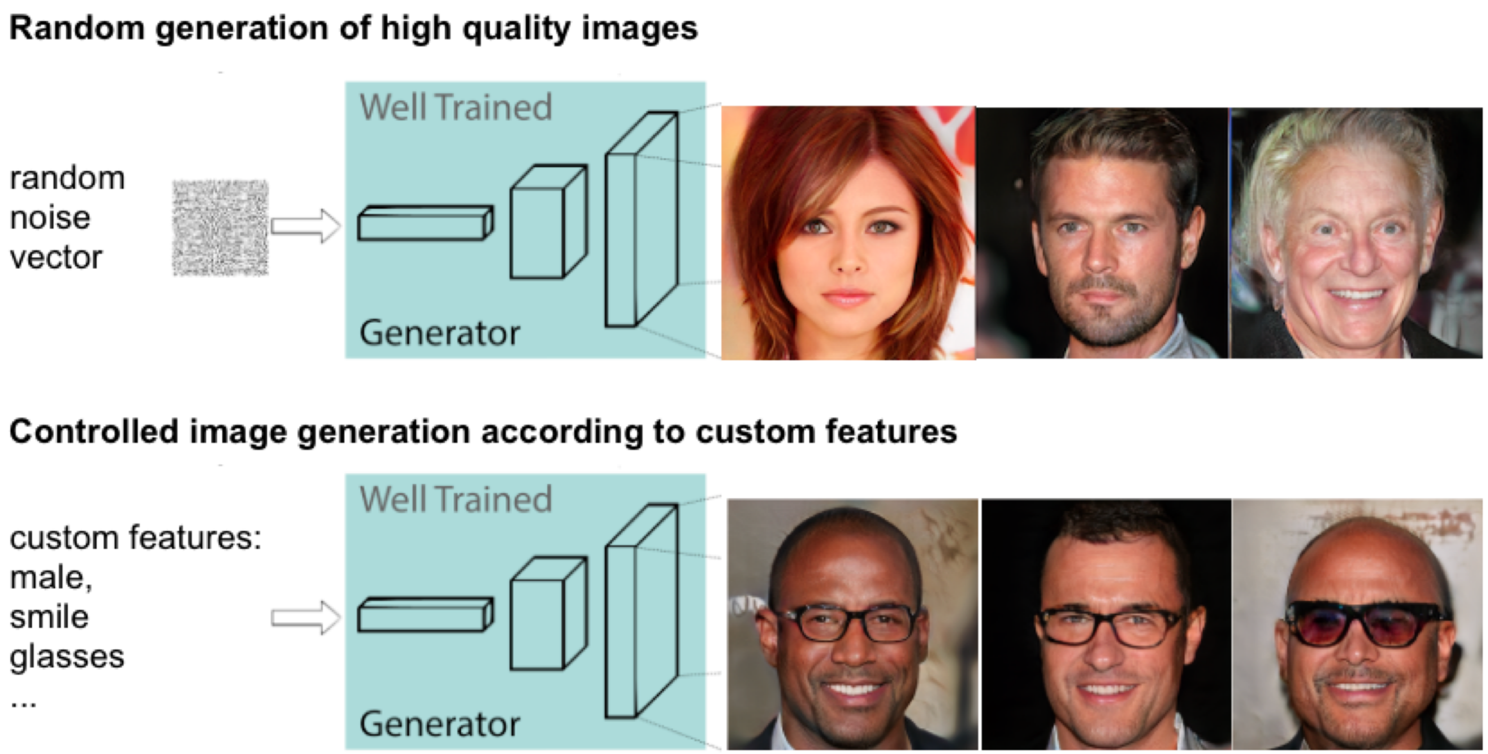
- May be efficient but
  - Simplification specific to one Linac type
  - Not a unique standardized method
  - Not easily generalisable to other Linac types (Cyberknife, Tomotherapy, FFF, etc)

GAN: Generative Adversarial Network

[Goodfellow, 2014]

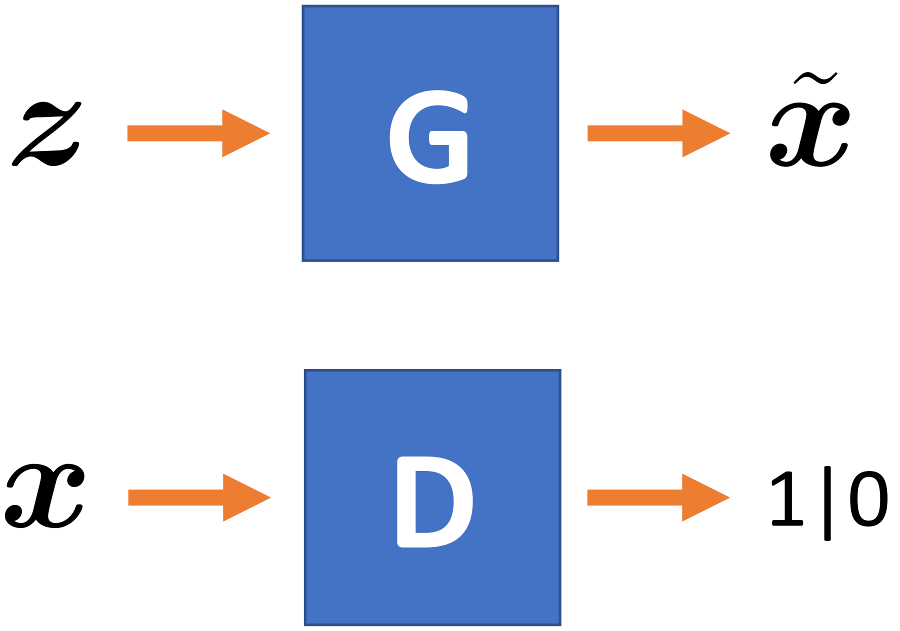
Goal: « learn » a multidimensional probability distribution

Initial application :
artificial images generator



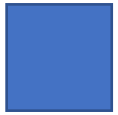
GAN: Generative Adversarial Network

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

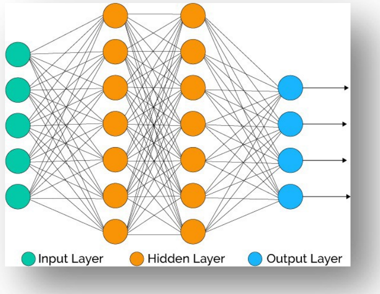


GAN: Generative Adversarial Network

- Training dataset $\boldsymbol{x} \in \mathbb{R}^d$
  - Dimension d=7 (E, X, Y, Z, dX, dY, dZ)
  - Samples of an unknown distribution p_{real}



=



Neural network

$$\boldsymbol{z} \rightarrow \boxed{\text{G}} \rightarrow \tilde{\boldsymbol{x}}$$

$$\boldsymbol{x} \rightarrow \boxed{\text{D}} \rightarrow 1|0$$

Alternate G and D optimisation updates

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:

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

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

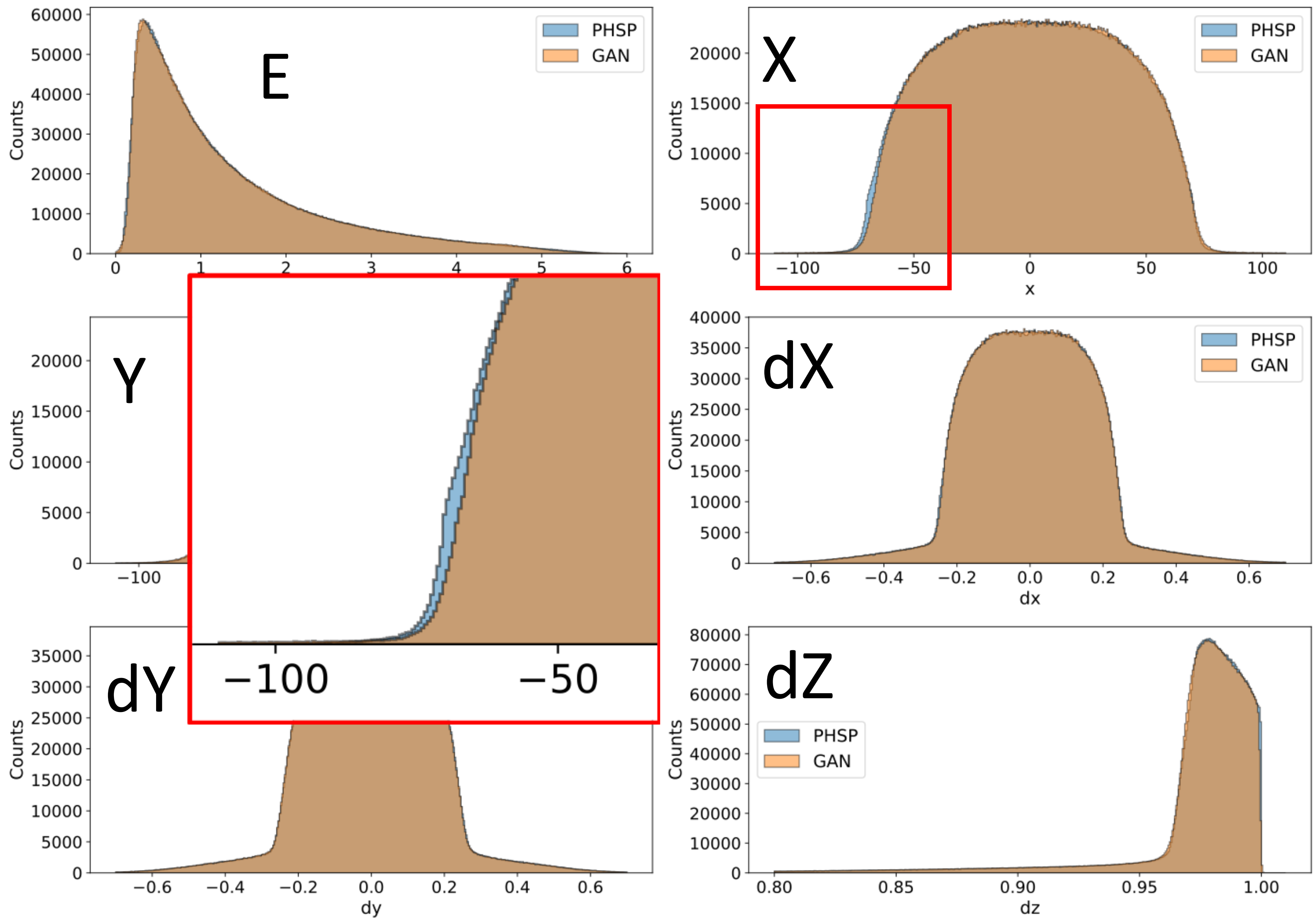
Experiments

PHSP downloaded on 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

Marginal distributions of the 6 parameters obtained from the reference PHSP and from the GAN, for Elekta 6MV linac.

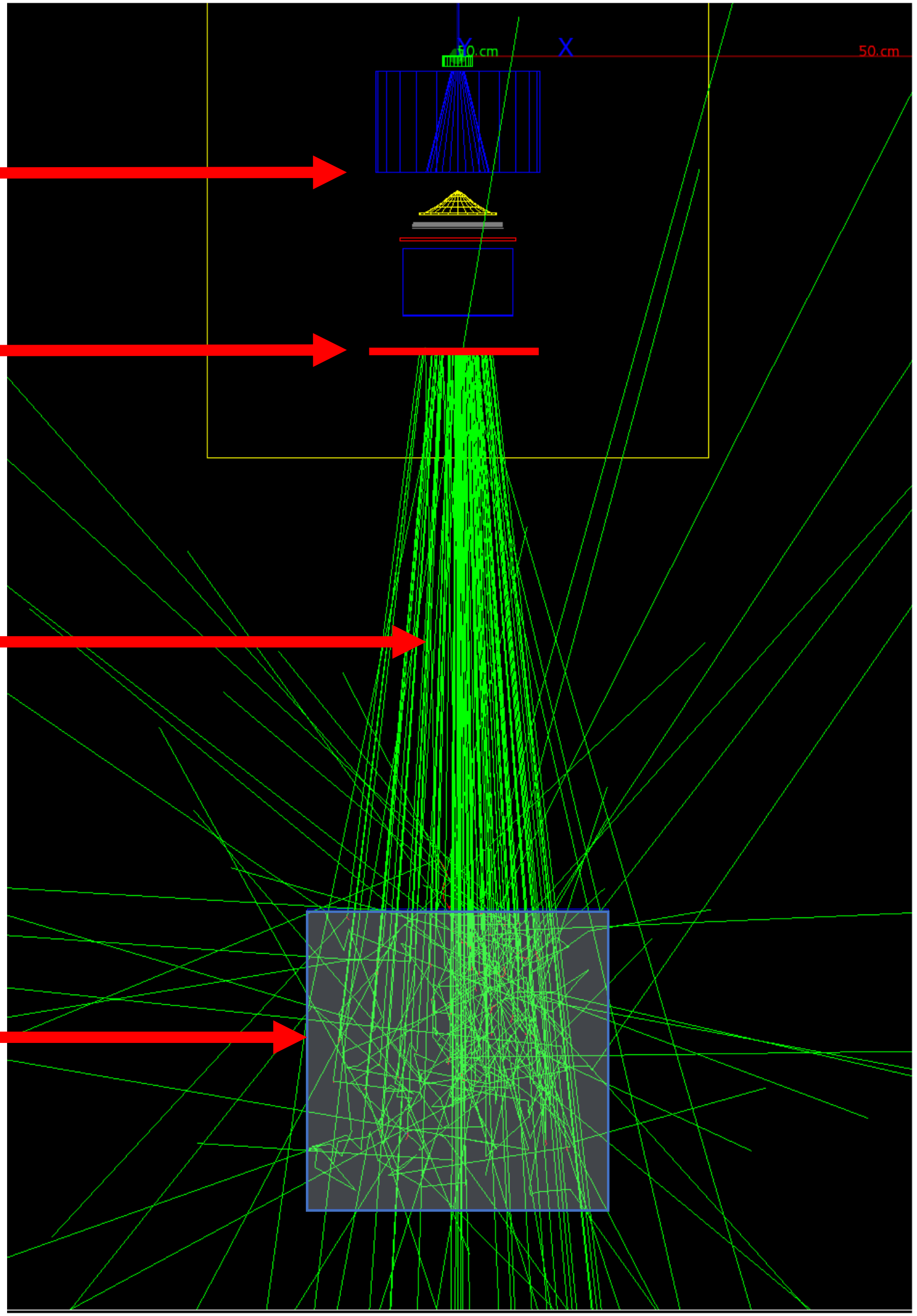


Results

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

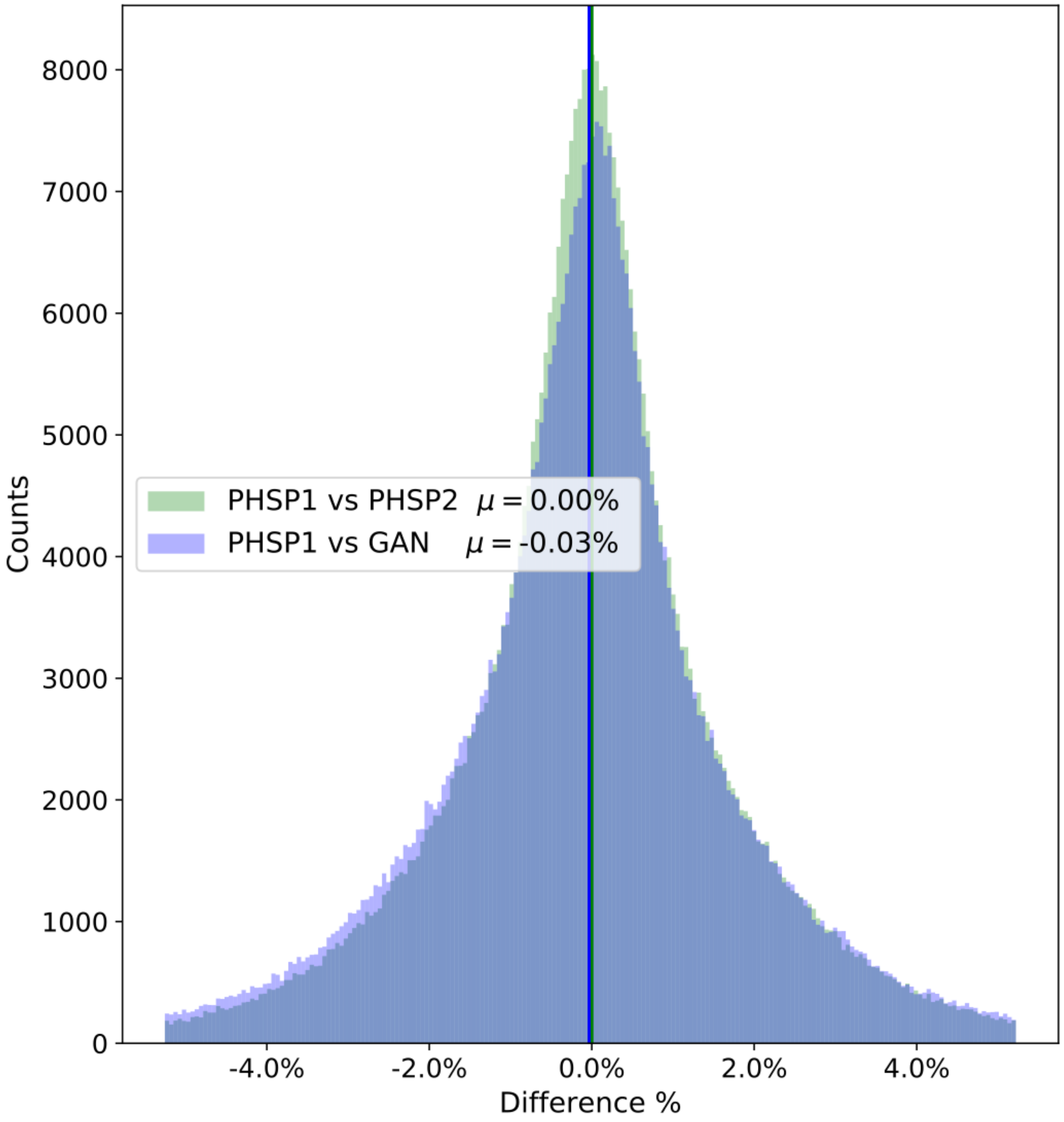
- Compare dose between:
  1. PHSP1 vs PHSP2
  2. PHSP1 vs GAN

- Voxel by voxel dose comparison



Results

Distributions of relative differences between
- PHSP1 and PHSP2
- PHSP1 and GAN



Vertical lines indicate the mean differences

Difference relative to the prescribed dose

Conclusion

- Using GAN to represent a Phase-Space is feasible
- Final GAN model: few MB (vs PHSP = 4 GB)
- Sufficient for dose computation
- Training is difficult: hyperparameters, 511 keV peak, …
- Soon available in GATE www.opengatecollaboration.org

- Perspectives :
    - Could it be learned from less particles ?
    - Detailed statistical analysis in progress
    - Other applications of GAN within MC simulations

PMB publication currently under revision

Thanks for your attention !

David Sarrut, Nils Krah, Jean-Michel Létang