Modeling detector digitization and read-out with adversarial networks

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Illustrations from the book "We have no idea" by D. Whiteson, J. Cham.
Cosmic RAYs Found In Smartphones Experiment

CRAYFIS experiment proposes usage of private mobile phones for observing Ultra-High Energy Cosmic Rays (UHECR):

› high energies: $> 10^{18}$ eV;
› distributed world-wide observatory;
› mobile phone’s camera as cosmic rays detector;
› cluster of mobile phones as intensive air shower detector.

Illustration of an intensive air shower produced by iron ion, 1 PeV, CORSIKA simulation, by J. Oehlschläger and R. Engel.

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Challenges

Physics:
› low signal event rate is expected:
  › background cosmic rays ($\approx 10^{13}$ eV): $> 1000$ per second per $km^2$;
  › UHECR ($\approx 10^{18}$ eV): less than once per year per $km^2$;
› an intensive air shower from UHECR occurs in less than microseconds;

Data processing:
› Getting realistic muon track images:
  › how muons interact with smartphone cameras (no ground-truth)?
› Tracking muons using smart phones:
  › shortage of computational power and storage space (mobile phones);
  › high frame rate processing is required ($\sim 10$ Hz);
  › limited throughput for selected images (end-user Wi-Fi $< 1$ Mbit/s);
Getting realistic images of muons (Parti-GAN)
The problem

A simulation with simplified geometry and without readout process is relatively simple (GEANT).

But there is no CMOS sensors details, precise enough for reliable simulation of particle-sensor interaction:

› various type of sensors;
› impossible to tune for every phone;
› muons are difficult to find & to prove.

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Let’s see if GANs can solve it

› Dataset:
  › simulated by GEANT images of energy deposition;
  › real images from radioactive source. no labels;
  › simple toy model adjusted to real data;
  › approximate ratio of signal/background: 0.001.

› Classical GAN - doesn’t deal with images as input and converges poorly;
› Cycle-GAN - should help finding 1:1 mapping, but does not solve all problems alone;
› Energy-Based - should help convergence, but still doesn’t work.

What if we add physics-based insights into the training of the generator?
Overwhelming amount of noise

Trick 1: importance sampling (real batch)

› increase number of events with higher signal probability in the batch reduce variance of the gradient;
› events are reweighted to keep original signal/noise ratio:

\[ \mathcal{L}_{\text{real}} = \frac{1}{n} \sum_{i} w_i l_{\text{real}}(y_i) \]

where:

› \( w_i \sim \frac{1}{p_i} \) - weight to compensate for change in sample distribution;
› \( p_i \) - sampling probability for \( i \)-th sample;
› we can use image brightness of the image as a proxy for \( p_i \).
Structure of a batch

\[ \begin{align*}
8 \times & \\
32 \times & \\
4 \times & \\
4 \times & \\
4 \times & 
\end{align*} \]

original

\[ \lambda = 0.2 \]

\[ \lambda = 0.5 \]

\[ \lambda = 1.5 \]
Helping GAN to learn the signal

- simulation does not account for signal event rate (just provides examples of interaction);
- signal event rate $\lambda$ in real observations is not known exactly;

Trick 2: introduce $\lambda$ as a GAN parameter to optimize;
- generate $m_k$ samples with $k$ events up to a large $k$;
- apply reweighting to redistribute number of events to match Poisson($\lambda$):

$$\mathcal{L}_{\text{pseudo}} = \sum_k w^k \sum_{j=1}^{m_k} l_{\text{pseudo}}(G(x^k_j))$$

where: $w^k = \frac{1}{m_k} \frac{\lambda^k e^{-\lambda}}{k!}$ - redistribution term.
Technical details. Overview

- Energy-Based GAN for [fast] convergence;
- Cycle-GAN to ensure bijection mapping between GEANT and generated samples;
- Batch reweighting to ensure convergence:
  - importance sampling for real images (decrease variance of gradient estimations);
  - physics process parameter $\lambda$ for generated samples.

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Constructing generator. Assumptions

› Observed samples are result of two independent ‘processes’:
  › various kinds of noise;
  › particle-sensor interaction;

› Track and noise energies can be added to each other:
  › simulation results can be added to various noise;

› The simulated process is local:
  › restricted perception field of generator (3 × 3);

› CMOS pixel brightness is of functional dependency on pixel energy deposit (adjacent pixels).
Generator structure

results of simulation

change of distribution

sum of energies

diffusion

energy to brightness
Cycle-GAN architecture (Parti-GAN is the same)
Parti-GAN Loss function

\[ L^X_D(X, X') + L^Y_D(Y, Y') + L^X_C(X, X'') + L^Y_C(Y, Y'') \]

\( X \) - bunch of GEANT images, \( Y \) - bunch of real images;
\( X' \) - 'real' images generated from \( X, G(X) \) in the batch;
\( Y' \) - 'GEANT' images generated from real images \( Y, \tilde{G}(Y) \) in the batch;
\( X'' : \tilde{G}(G(X)), Y'' : G(\tilde{G}(X)) \);
\( L^X_D, L^Y_D \) - EBGAN loss functions;
\( L^X_C, L^Y_C \) - cycle loss functions (MSE);
\( X \) are weighted by physical sampling coefficients;
\( Y \) are weighted by importance sampling coefficients.
Parti-GAN results
Results cross-check: pixel intensity
Summary

Parti-GAN learns actual physical process ($\lambda$) + preprocessing algorithm:

- corrections on electron drift;
- thermal noise, readout noise;
- physical/hardware readout systems.

Parti-GAN matches simulation to real observations ("unpaired image translation")

Parti-GAN is based on CycleGAN with EBGAN loss function + importance sampling

It can generate realistic images of muon tracks for any phone model!
Thank you for attention!
Backup
CRAyFis collaboration

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