NATIONAL RESEARCH UNIVERSITY

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The Faculty of Computer Science
The LAboratory of Methods for Big Data Analysis (LAMBDA)

FAST SIMULATION OF THE ELECTROMAGNETIC CALORIMETER RESPONSE USING SELF-ATTENTION GENERATIVE ADVERSARIAL NETWORKS

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PROBLEM STATEMENT

Simulation of ECAL response via Geant4

Main goal is to **generate energy distribution in ECAL**:

- Faster than Geant4
- Improve performance of the model by V. Chekalina et al.[1] and F. Sergeev et a

Input:

- ParticlePoint (x,y,z) – known starting point location
- ParticleMomentum (p_x, p_y, p_z) –known momentum

Output:

- Consider 20 mm cell to fit both 40 mm and 60 mm cells
- EnergyDeposit – 30×30 energy distribution matrix, shower width < 600 mm

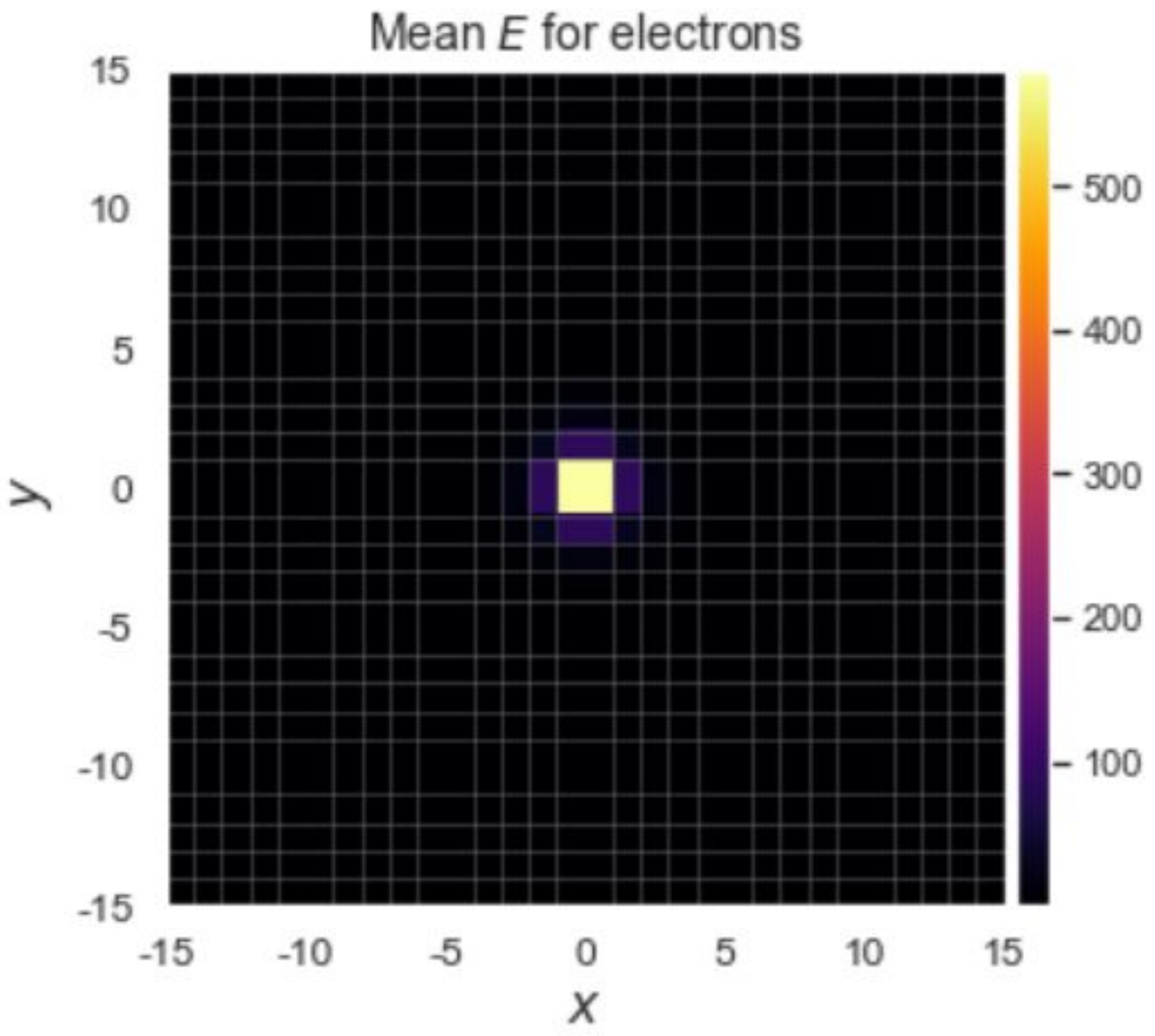


Fig. 1 Example of mean response generated by Geant4 [1]

[1] Generative Models for Fast Calorimeter Simulation.LHCb case. Chekalina, V., Orlova, E., Ratnikov, F., Ulyanov, D., Ustyuzhanin, A., & Zakharov, E. 2018.

CONDITIONAL GENERATIVE ADVERSARIAL NETWORK

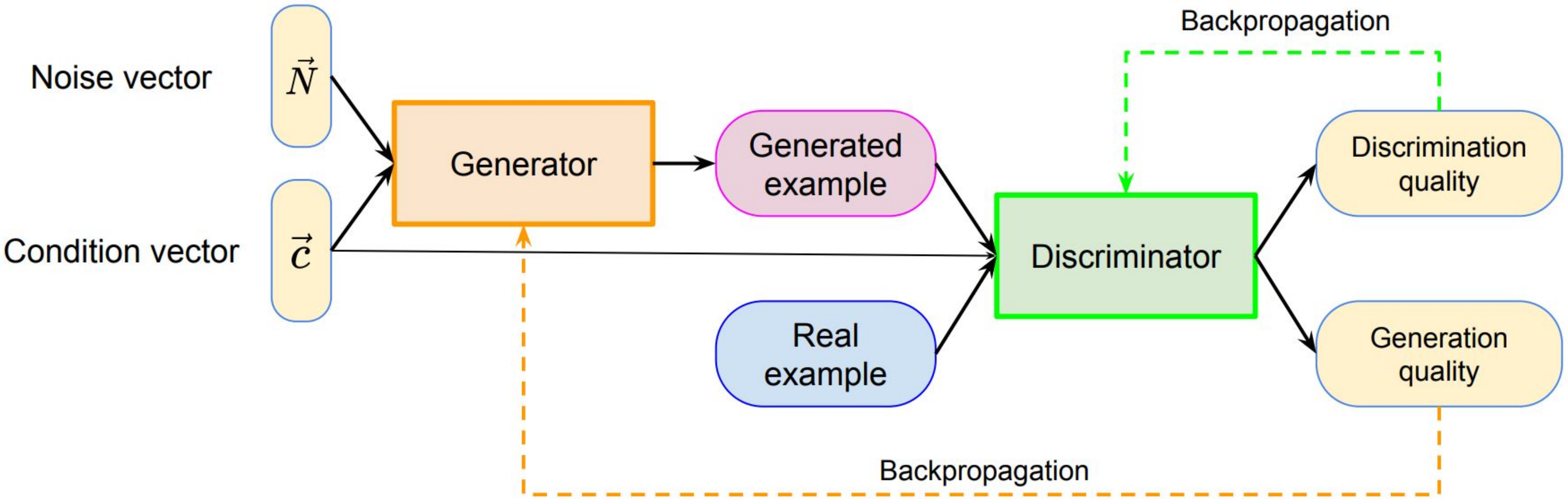


Fig. 2 Example of CGAN architecture [2]

[2] Fast simulation of the LHCb electromagnetic calorimeter response using VAEs and GANs Fedor Sergeev et al 2021 J. Phys.: Conf. Ser. 1740 012028

RELATED WORK

"Generative Models for Fast Calorimeter Simulation: the LHCb case"

V. Chekalina, E. Orlova, F. Ratnikov, D. Ulyanov, A. Ustyuzhanin, E. Zakharov

- Achievs $\times\ 10^5$ speed increase over Geant4
- Shows good agreement for primary cluster characteristic
- Needs quality metrics

" Fast simulation of the LHCb electromagnetic calorimeter response using VAEs and GANs"

F. Sergeev, N. Jain, I. Knunyants, G. Kostenkov, E. Trofimova

- Uses PRD-AUC score for quality evaluation
- Shows that additional techniques improves performance

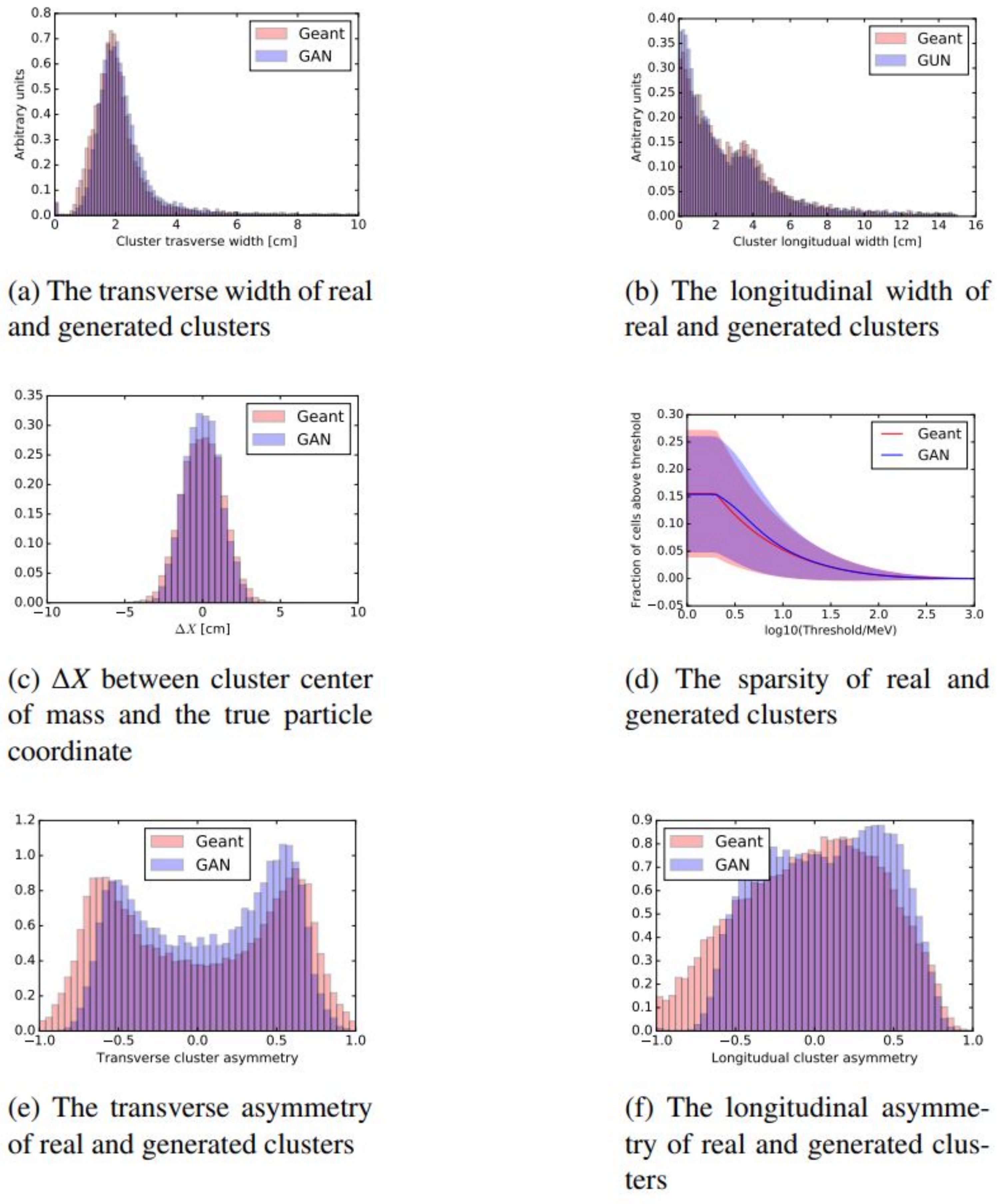


Fig. 3 Generated images quality evaluation including described physical characteristics. [2]

We try to apply other techniques and architectural approach to improve the results and boost the PRD-score

PROBLEMS

- CNN filters are good at exploring spatial locality information, but the receptive fielc
- Its difficult to find relationship between distant regions
- Fails at capturing geometric or structural patterns

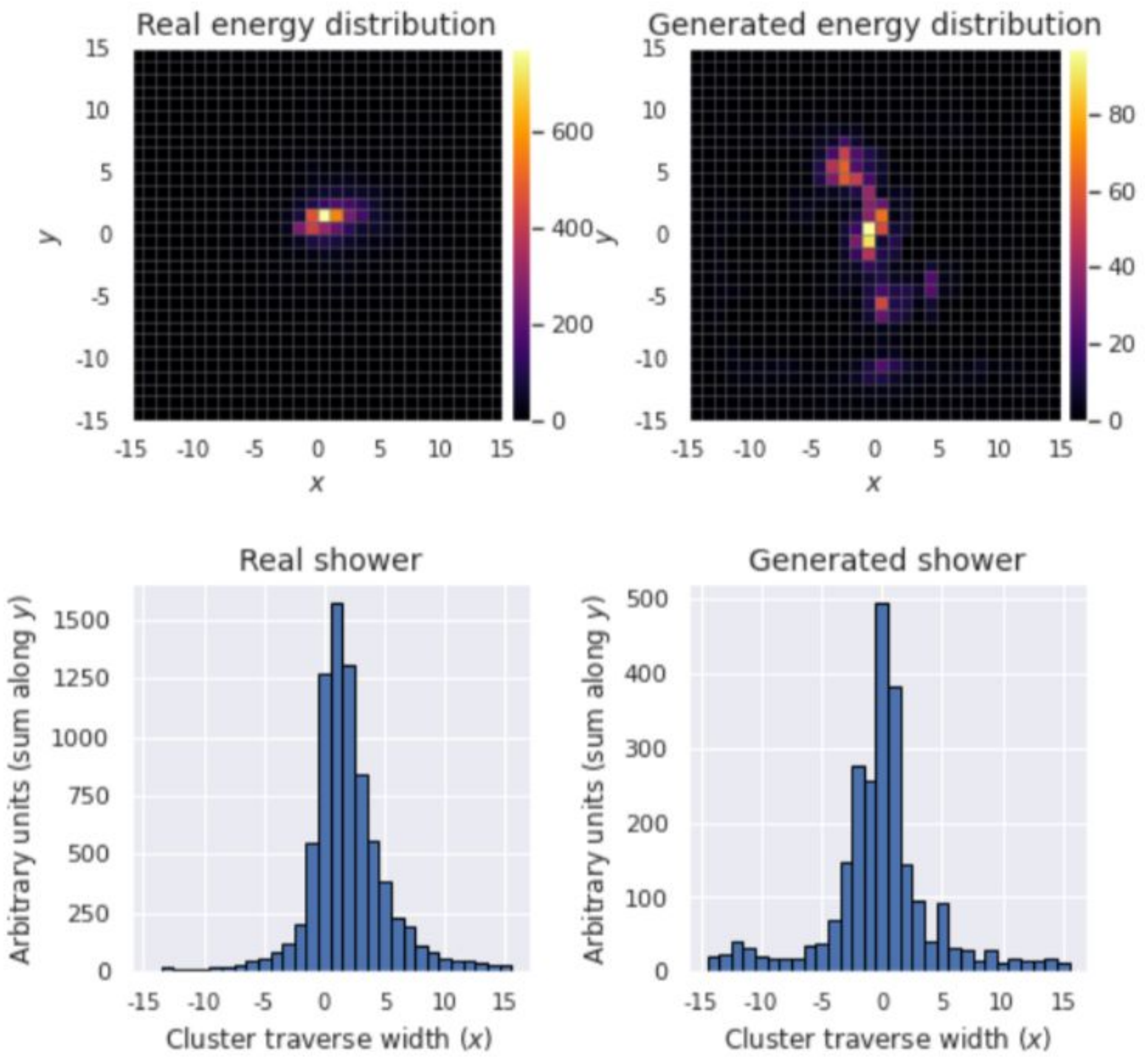


Fig. 3 Example of generated image [2]

Self-attention may help to improve the shape of generated clusters

SELF-ATTENTION GAN

The image features from the previous hidden layer x ∈ R C×N are first transformed into two feature spaces

- $g(x) = W_g x$
- $f(x) = W_f x$
- $s_{ij} = f(x_i)^T g(x_j)$
- $\beta_{j,i} = \frac{\exp(s_{ij})}{\sum_{\{i=1\}}^{N} \exp(s_{ij})}$

$\beta_{j,i}$ indicates the extent to which the model attends to the i-th location when synthesizing the j-th region

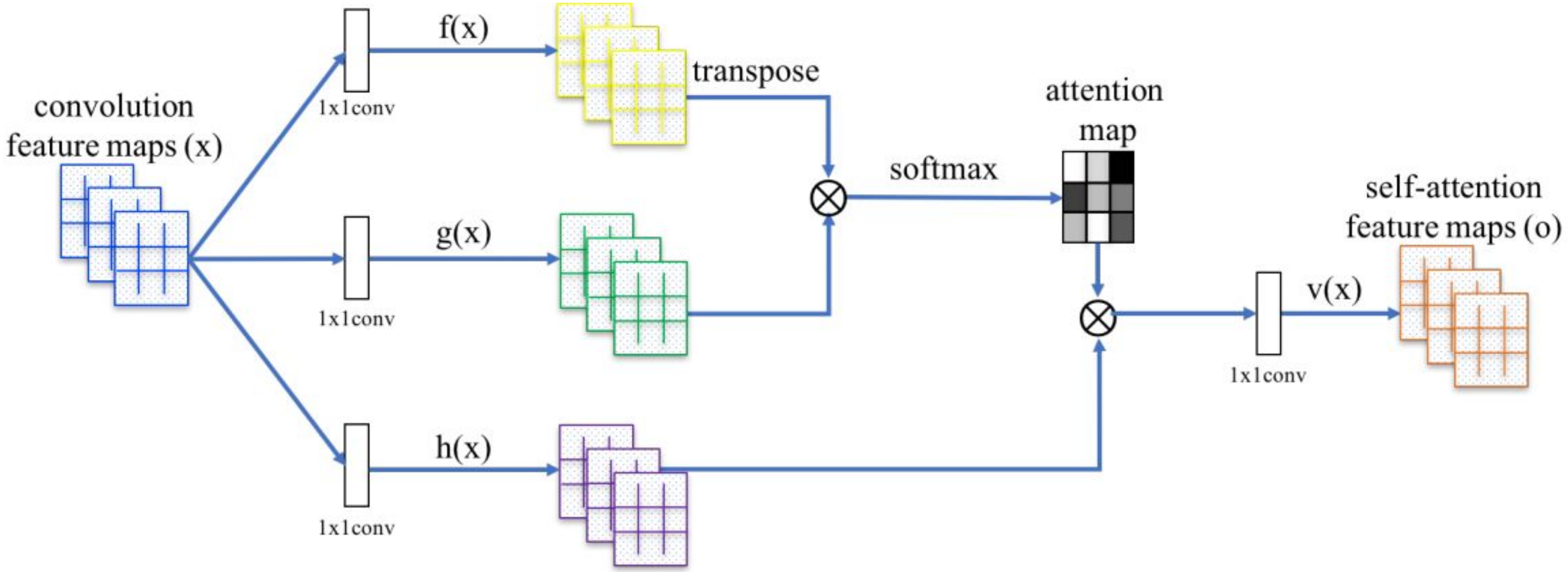


Fig. 4 The self-attention module for the SAGAN [3]. The ⊗ denotes matrix multiplication.

[3] Zhang H. et al. Self-attention generative adversarial networks //International conference on machine learning. – PMLR, 2019. – C. 7354-7363.

PROPOSED ARCHITECTURE

- The attention module has been applied to both the generator and the discriminator, as well as spectral norm.
- Spectral Normalization[4] does not require any hyper-parameter tuning
- Models are trained by minimizing the hinge version of the adversarial loss

$$
\begin{aligned}
L_D = & -\mathbb{E}_{(x,y)\sim p_{data}}[\min(0, -1 + D(x,y))] \\
& -\mathbb{E}_{z\sim p_z, y\sim p_{data}}[\min(0, -1 - D(G(z),y))], \\
L_G = & -\mathbb{E}_{z\sim p_z, y\sim p_{data}} D(G(z), y),
\end{aligned}
$$

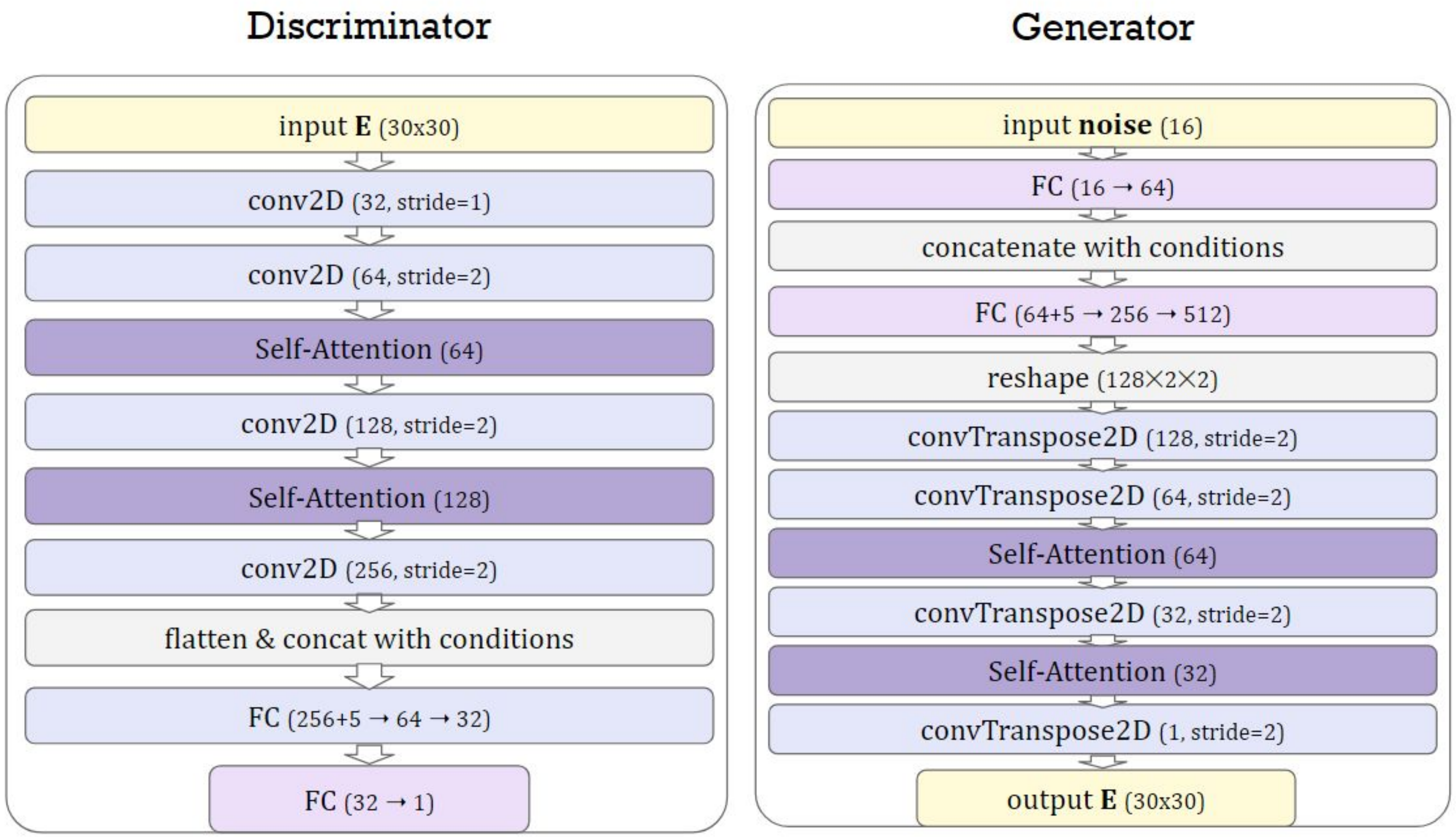


Fig. 5 The proposed architecture of GAN.

[4] Miyato T. et al. Spectral normalization for generative adversarial networks //arXiv preprint arXiv:1802.05957. – 2018.

PRD-AUC

- **P, Q** – real and generated distributions
- $\boldsymbol{\nu_Q}, \boldsymbol{\nu_P}$– loss in precision and loss in recall
- **α, β** ∈ (0,1] – precision and recall

$$P = \beta\mu + (1-\beta)\nu_P \quad Q = \alpha\mu + (1-\alpha)\nu_Q$$

- **P**recision **R**ecall **D**istribution [5] – all attainable pairs (**α, β**)
- **PRD A**rea **U**nder **C**urve (**Q, P**) characterizes trade-off between precision and recall

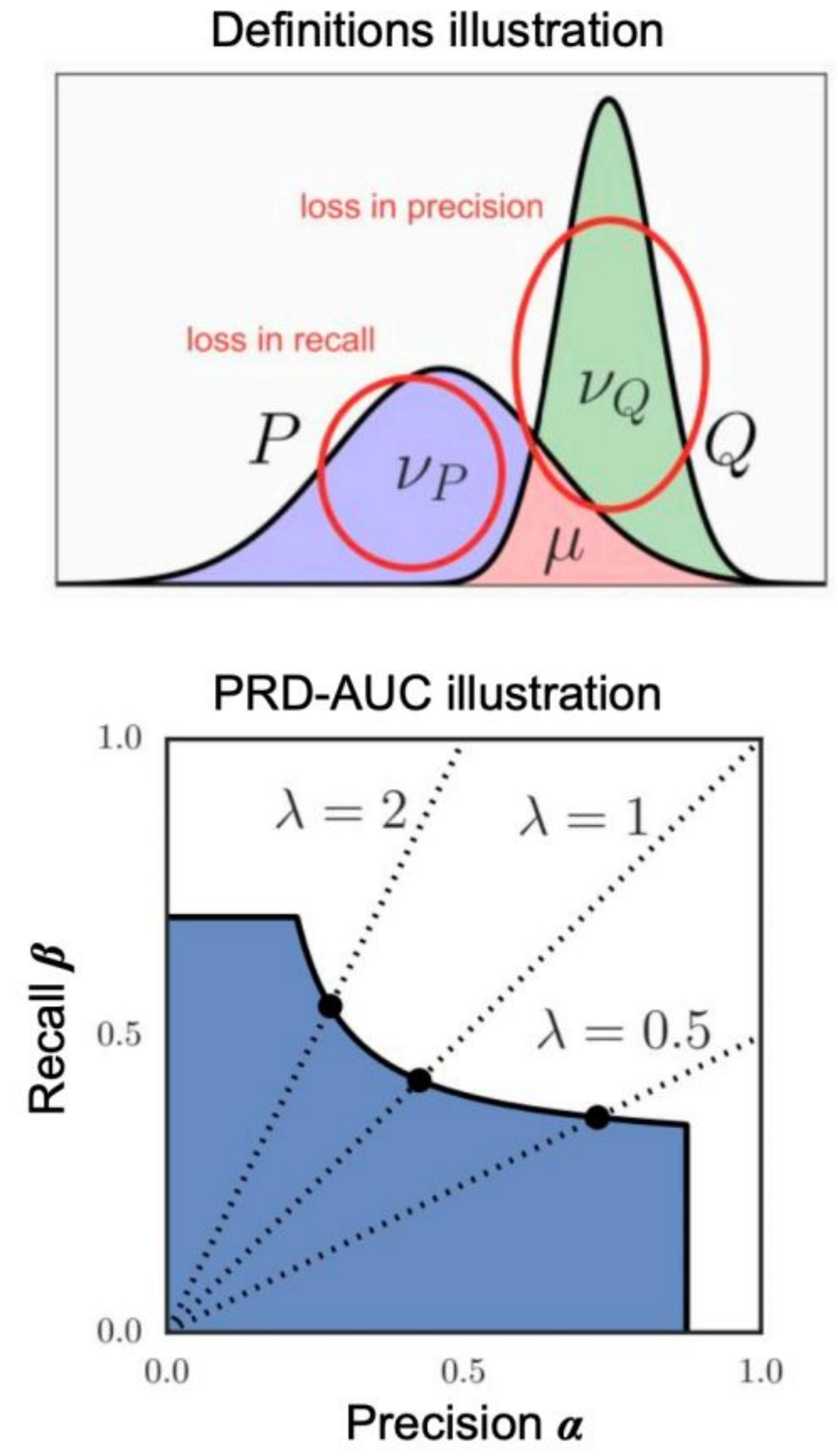


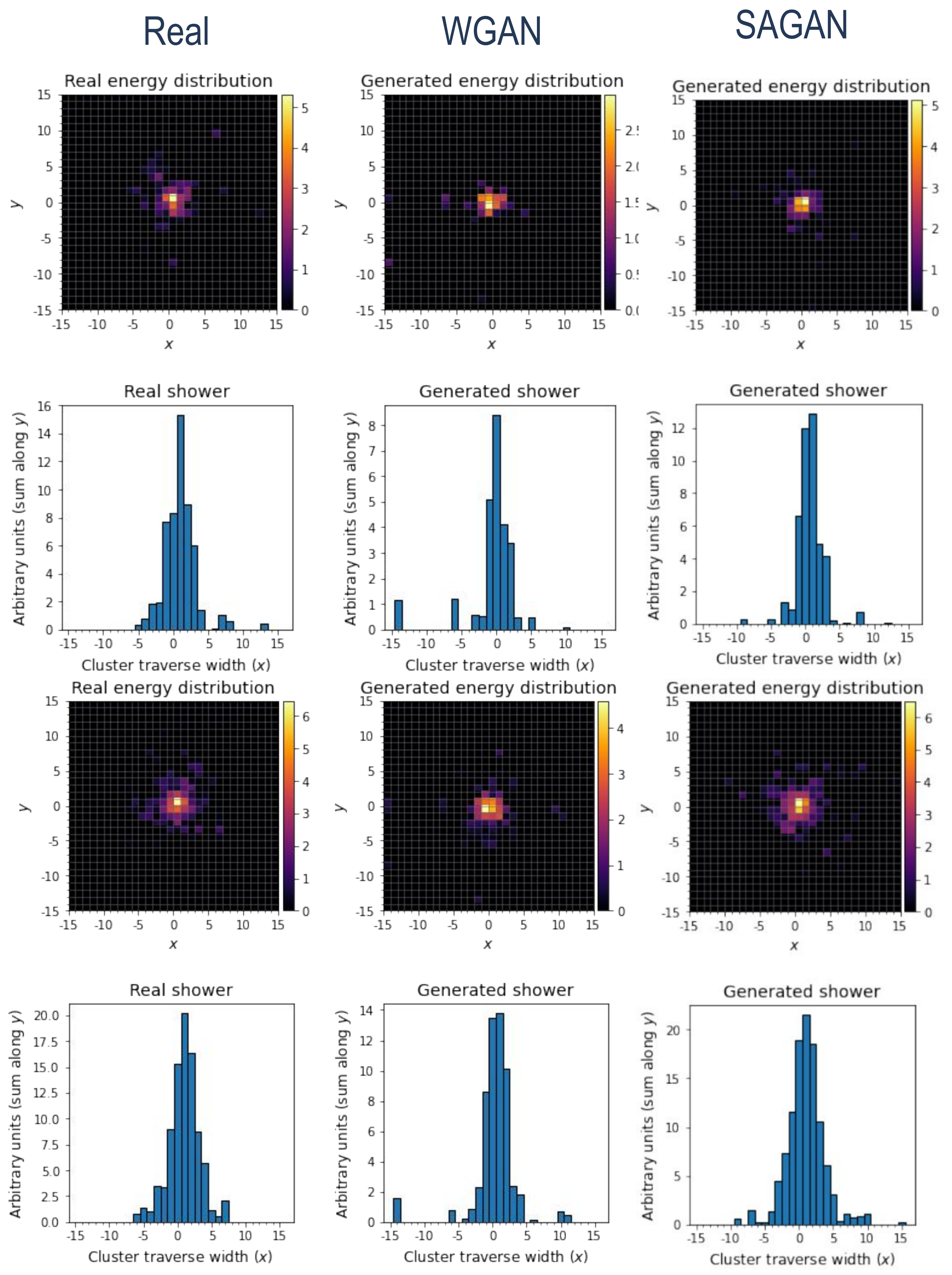
Fig. 5 The proposed architecture of GAN.

[5] Sajjadi, M. S., Bachem, O., Lucic, M., Bousquet, O., & Gelly, S. (2018). Assessing generative models via precision and recall. arXiv preprint arXiv:1806.00035.

RESULTS

Model	Physics PRD-AUC	Raw Images PRD-AUC
WGAN	0.936	0.971
SAGAN+SN D	0.895	0.901
SAGAN+SN G and D	0.948	0.975

- SAGAN with Spectral Normalization in Generator and Discriminator showed the best performance in terms of PRD-AUC
- Both RAW and Physical score were boosted
- Spectral Normalization performed worse than Gradient Penalty in case of WGAN



CONCLUSION AND FUTURE WORK

- Self-attention module improves the performance of previously published model, it shows promising results and can be further studied
- PRD-AUC can be calculated fast, but should be replaced by proper quality metrics that take physics background into account
- Other attention-style techniques should be studied and Transformer-based GAN can be a possible architecture
- Different preprocessing approaches should be compared

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