Applying attention mechanism in fast ZDC simulations

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Attention mechanism



Vision Transformer (ViT)



Used architectures

Generative Adversarial Networks

Variational Autoencoders



Proposed models



Han Zhang et al. 2018. *Self-Attention Generative Adversarial Networks*. Remote Sensing 14, no. 10: 2425. Yifan Jiang et al. 2021. *TransGAN: Two Pure Transformers Can Make One Strong GAN, and That Can Scale Up*. CoRR abs/2102.07074.

Proposed models



Evaluation results

Model	My results ¹		Article	
	Wasserstein	MAE	Wasserstein	MAE
Original data	_	_	2.89	6.59
$\mathrm{GAN}^{2,4}$	13.72	86.20	6.95	68.27
VAE	16.68	18.91	14.92	23.13
SAE	24.09	27.24	7.91	13.50
${ m GAN}+{ m Cond}^{2,4}$	14.96	69.40	_	_
$\mathrm{GAN} + \mathrm{ViT^3}$	×	×	_	_
$SA-GAN^4$	52.31	86.81	_	_
TransGAN	3.95	25.42	_	—
VAE + Cond	6.53	14.78	_	_
VAE + ViT	16.97	19.35	_	_
VAE + TransDec	8.35	15.88	_	_
VAE + Cond + TransDec	8.33	15.16	_	_
TransVAE	9.19	15.25	_	_
VAE + MLP Cond	5.59	14.61	_	_

¹ Best result from models saved after each training epoch
 ² Unstable results, metrics vary significantly in successive epochs
 ³ Impossible to train, it collapses in the first epochs
 ⁴ The generated images do not visually resemble the original data

Evaluation results

TransGAN (best Wasserstein) $\begin{bmatrix} 4 \\ 3 \\ 2 \\ 1 \\ 0 \end{bmatrix} \begin{bmatrix} 0.6 \\ 0.4 \\ 0.2 \\ 0.0 \end{bmatrix} \begin{bmatrix} 4 \\ 3 \\ 2 \\ 1 \\ 0 \end{bmatrix} \begin{bmatrix} 4 \\ 3 \\ 2 \\ 1$

VAE + MLP Cond (best MAE)



Conclusions and future work

- GANs are difficult to train and sometimes have poor quality results.
- VAE with MLP network for conditional variables achieves the best results .
- Reproducing the same results as in the article.
- Searching for new models normalizing flows?
- New metric?