

Generative Adversarial Networks GANs

The theoretical research of generative adversarial networks: an overview

Yanchun Li ^a, Qiuzhen Wang^{b,†}, Jie Zhang ^c, Lingzhi Hue, Wanli Ouyang

- ❑ Variants GANs
- ❑ Hybrid GANs

By Antonio Leal
November-2023

Variants GANs

(adding regularization and normalization)

Table 1

An overview of GAN variants.

Reach Topic	Reference
Extending the objective	f-GAN [34], b-GAN [45], Learning in implicit generative model [46]
Training Dynamic	Local GAN [35], ConOpt [47], GAN-Stability [48]
Different divergence	WGAN [36], McGAN [38], GAN [1], Least squares GAN [49], Geometric GAN [50]
Adding regularization	WGAN-GP [37], Loss-Sensitive GAN [51], Fisher GAN [52], DRAGAN [53], SNGAN [54], BigGAN [55]

Variants GANs

Extending the objective

Extending the divergence

measure of how different the probability distributions generated by the generator are and the actual distributions of the data

Extending the classification function

additional component added to the model to improve the training process

Matching the density ratio

how well the data generated by the GAN reflects the real data.

Training Dynamics

adding regularization and normalization of parameters

Métodos Aprimorados:

Diferent divergence

Jensen-Shannon, Kullback–Leibler, Reverse KL, Squared Hellinger
Pearson

Adding regularization

including additional terms in loss functions during training to avoid problems such as overfitting and instability.

(*) other techniques: add instance noises, feature matching, per-pixel
feature vector normalization for generator, batch normalization, layer
normalization

Hybrid GANs

(adding network architectures)

Table 2

An overview of hybrid GANs.

Combined network	Reference
Encoder VAE	ALI [56], BiGAN [57], VEEGAN [39], MRGAN [58], AGE [59] VAEGAN [60], AAE [61], AVB [62], α -GAN [40], On Unifying Deep Generative Models [63]
Energy model	EBGAN [41], BEGAN [41], DFM [64], MAGAN [65], MEG [66]

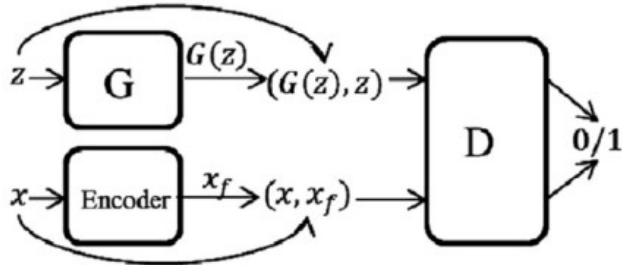
Hybrid GANs

Encoder:

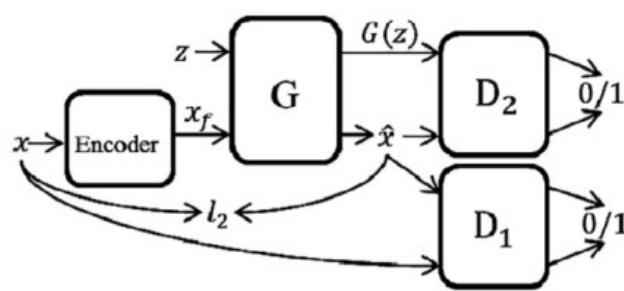
Add additional encoder

Bidirectional

Multiple data resolution



(b) BiGAN/ALI

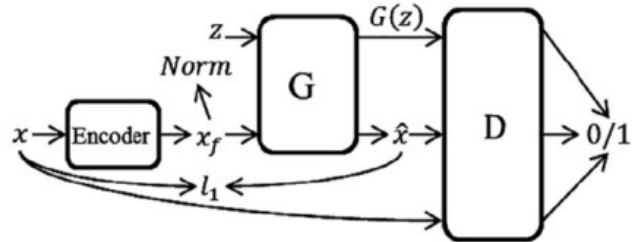


(h) MRGAN

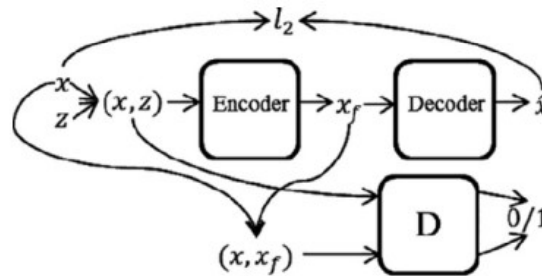
Hybrid GANs

VAE:

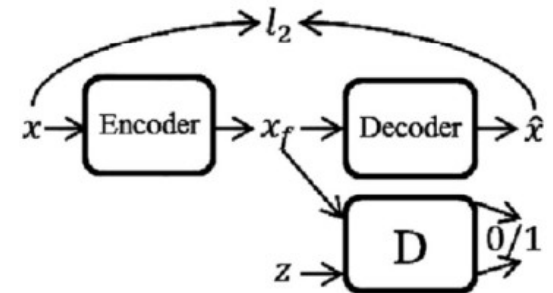
Bayesian inference
Autoencoders



(j) VAEGAN



(a) AVB

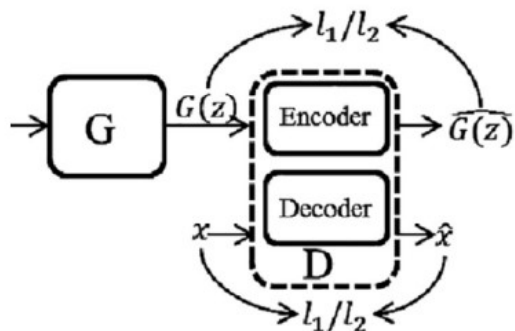


(c) AAE

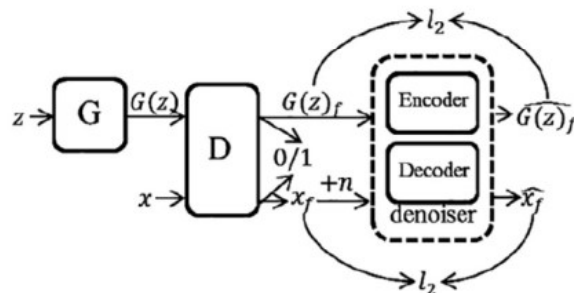
Hybrid GANs

Energy Model:

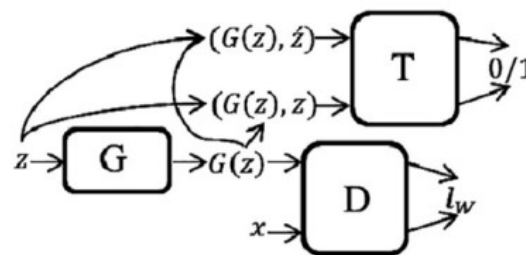
Treats the DISCRIMINATOR as a function of energy
(low values for real samples and high values for generated samples)
More flexible loss function



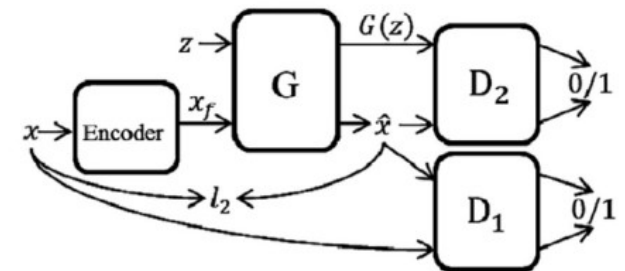
(e) BEGAN/EBGAN



(f) DFM



(g) MEG



(h) MRGAN