GAN

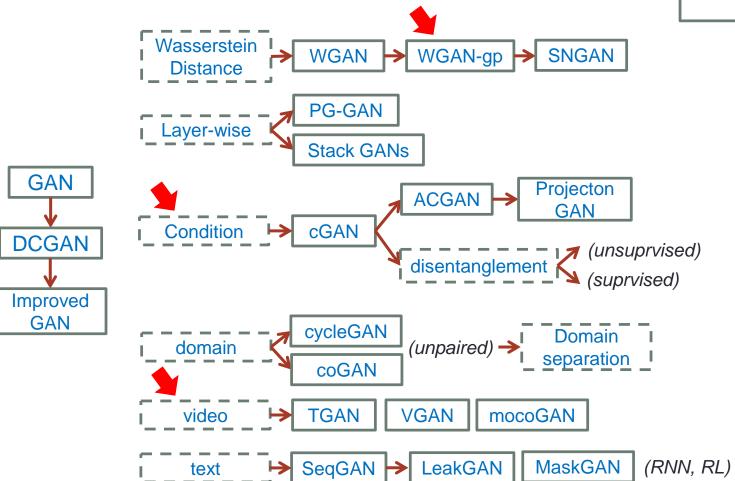
2018/7/11

Preface

- Topics
 - Experiences & tricks
 - Paper Survey
 - MuseGAN, MidiNet Review
- Outline
 - GAN Review
 - Road Map
 - Condition
 - Video

Road Map





GAN Review

Data & Generator

Discriminator

Training

Testing

Discussion

Review: How to start a GAN project?

- Data
- Generator
- Discriminator
- Training
- Testing
- State-of-the-art?
- ♠ [-] ajmooch 6 points 3 months ago
- Projection discriminator + SN-GAN + progressive growing is probably our best bet at the moment for highest-fidelity high-res images, but the resources to do an ImageNet-level variety of classes at high res will probably be pretty substantial (just to get everything tuned, let alone to train it).
- Models: DCGAN WGAN-gp SNGAN

^{*} https://www.reddit.com/r/MachineLearning/comments/890prh/r_memgen_memory_is_all_you_need_generative/

Data & Generator

- No matter what your task is, Normalization on data is necessary.
- The activation of the output layer of the generator depends on the range of the data
 - Bounded

Unbounded

zero means unit variance logarithm (ex: on spectrogram)

 $\mathcal{N}(\mu,\,\sigma^2)$

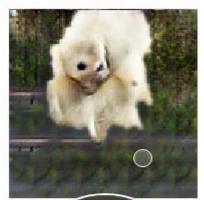
leaky ReLU, ReLU?



- SharedArray & Shuffle data by index at runtime
- z: sampled from a Gaussian distribution

Generator

- Batch Normalization is essential to the quality
- Upsampling Layers:
 - Deconvolution (transposed convolution)
 - The most common method
 - Checkerboard artifacts?
 - Resize-Convolution
 - ex: PG-GAN uses nearest neighbor upscaling
 - Pixel Shuffling
 - Super resolution





Salimans et al., 2016 [2]

 Residual Blocks can enhance the quality as well, especially when the size of the images is large and the corresponding network is deep.

^{*} **PG-GAN:** https://arxiv.org/pdf/1710.10196.pdf

^{*} https://distill.pub/2016/deconv-checkerboard

Discriminator



Loss function:

Original GAN loss: DCGAN

$$\min_{G} \max_{D} V(D,G) = \mathbb{E}_{\boldsymbol{x} \sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{z} \sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))].$$

D Loss:
$$-\log (D(X)) - \log (1 - D(G(z))$$

G Loss: $-\log (D(G(z)))$



In practice...

Discriminator

```
WGAN loss: SNGAN

D Loss: (D(X)) + (D(G(z)))

Minimize!!
```

remove log

Gradient penalty: WGAN-gp

G Loss: - (D(G(z)))

```
D Loss: - (D(X)) + (D(G(z))) + (||\nabla_x D(x)|| - 1)^2
G Loss: - (D(G(z))) penalty Minimize!!
```

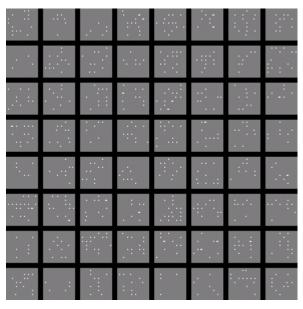
- Parameter Updating:
 - WGAN-gp update G once every 5 updates of D

Training

- When to stop?
- How to monitor the training procedure?
- GAN Losses cannot truly reflect the quality (even for WGAN)
- Generate samples along training!

Samples/*.png:

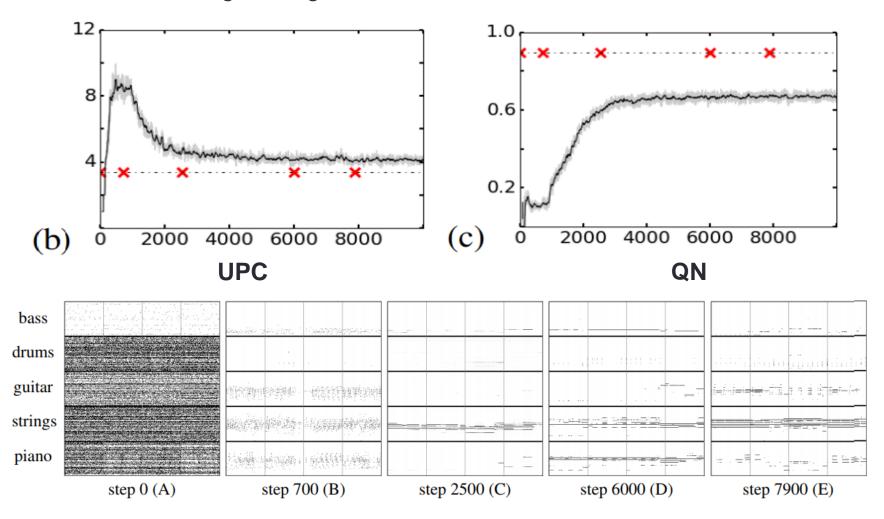
sample_2.png	2018/7/7 下午 06:42
sample_142.png	2018/7/7 下午 06:43
sample_282.png	2018/7/7 下午 06:43
sample_422.png	2018/7/7 下午 06:43
sample_562.png	2018/7/7 下午 06:43
sample_702.png	2018/7/7 下午 06:43
sample_842.png	2018/7/7 下午 06:44
sample_982.png	2018/7/7 下午 06:44
sample_2002.png	2018/7/7 下午 06:45
sample_4002.png	2018/7/7 下午 06:48
sample_6002.png	2018/7/7 下午 06:50
sample_8002.png	2018/7/7 下午 06:53
sample_10002.png	2018/7/7 下午 06:55



(SNGAN on CIFAR10)

Early Stopping

Evaluate along training!



^{*} from MuseGAN

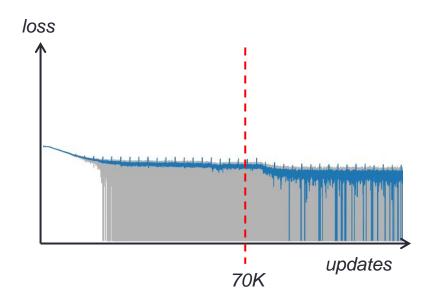
Training

• For the first time, train the model for a longer period of time and monitor the procedure.

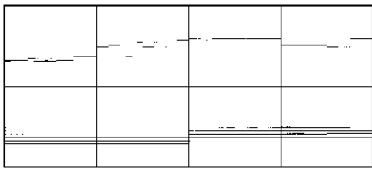


Mode collapse

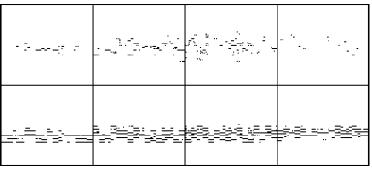
Degeneration



(70K updates)



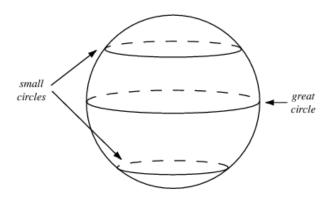
(130K updates)

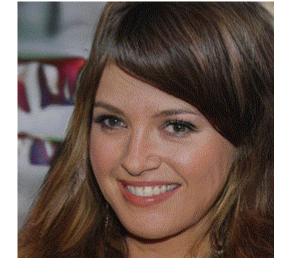


^{*} MuseGAN (with WGAN-gp), lead sheet generation

Testing

Interpolation: Spherical (instead of linear)





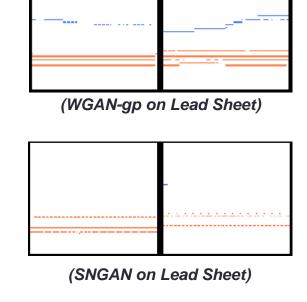
- Dropout on?
 - Image-to-Image (https://arxiv.org/pdf/1611.07004v1.pdf) turns on when testing
 - Later works seldom use it

^{*} GAN hacks: https://github.com/soumith/ganhacks

^{*} Figure: from https://github.com/ptrblck/prog_gans_pytorch_inference

Discussion

- So, which model should I use?
- Loss
 - For image, SNGAN outperforms others in both of the efficiency and the quality.
 - For discrete (binary) representation, only WGAN-gp can generate results successfully.
- Network design
 - Deconvolution is simple but powerful
 - If you aim to generate images with higher qualities, try to use residual blocks and resize-upsampling layers.



Conditional GANs

How to apply condition Tag? Disentanglement Discussion

How to apply condition?

- Input Concatenation
 - cGAN: https://arxiv.org/pdf/1411.1784.pdf
- Feature Map Concatenation
 - DCGAN: https://github.com/carpedm20/DCGAN-tensorflow
- Auxiliary Classifier
 - ACGAN: https://arxiv.org/pdf/1610.09585.pdf
- Encoder
 - S² GAN, Generative Adversarial Text to Image Synthesis
 - MuseGAN/MidiNet: https://arxiv.org/pdf/1703.10847.pdf
 - FTGAN: https://arxiv.org/pdf/1711.09618.pdf
- Projection Discriminator (ICLR, 2018)
 - https://arxiv.org/pdf/1802.05637.pdf
- Principle:
 - Both of G and D need to receive the conditional information.

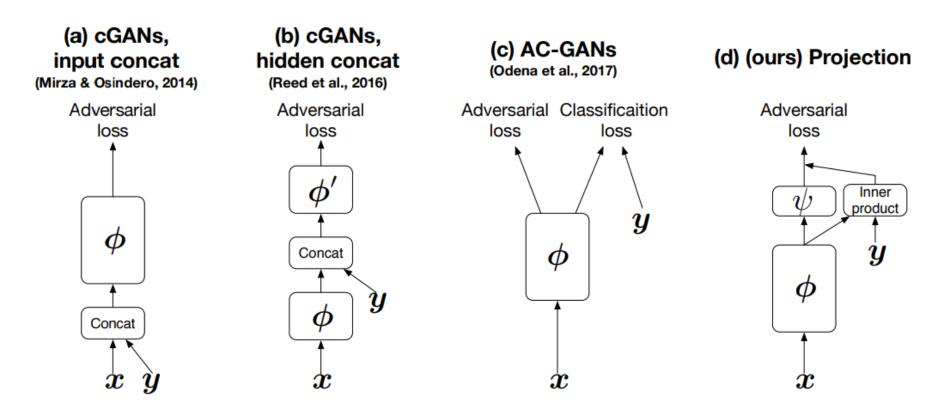


Figure 1: Discriminator models for conditional GANs

Concatenation

The most common method, naive but practical.

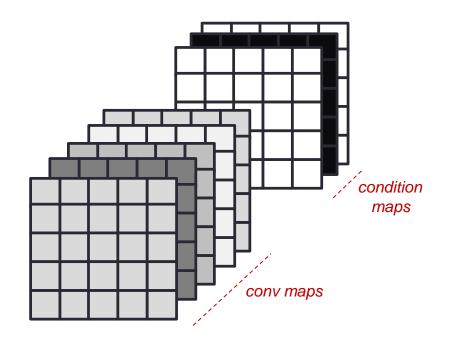
vector concatenation (for linear layer, input z)





one-hot label

Feature map concatenation (for convolution layer)





(SNGAN on MNIST)

Auxiliary Classifier

• Or with only auxiliary loss

Adversarial loss

Cross Entropy (Categorical)

Mean Square Error (Continuous)

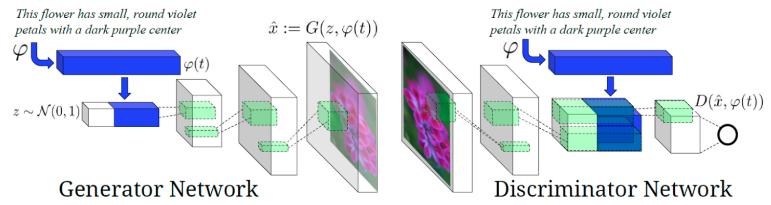
Classifier (optional)

- Where should I concatenate labels? Every layer in G & D?
 - It depends. Layers which is responsible for higher level features have priorities.
- Conditional generation is still a challenging task.
- SNGAN + projection discriminator achieve promising results.

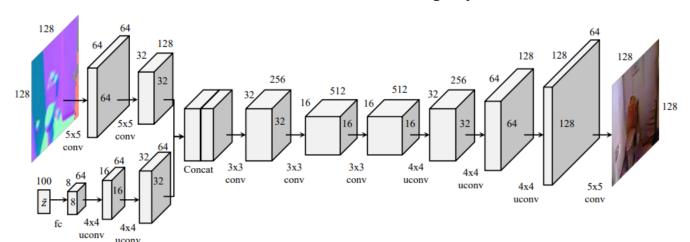
^{*} cods: https://github.com/pfnet-research/sngan_projection

Encoder

- For more complex conditional vectors
- Motivation: guide the generation process



Generative Adversarial Text to Image Synthesis



S² GAN: Generative Image Modeling using Style and Structure Adversarial Networks

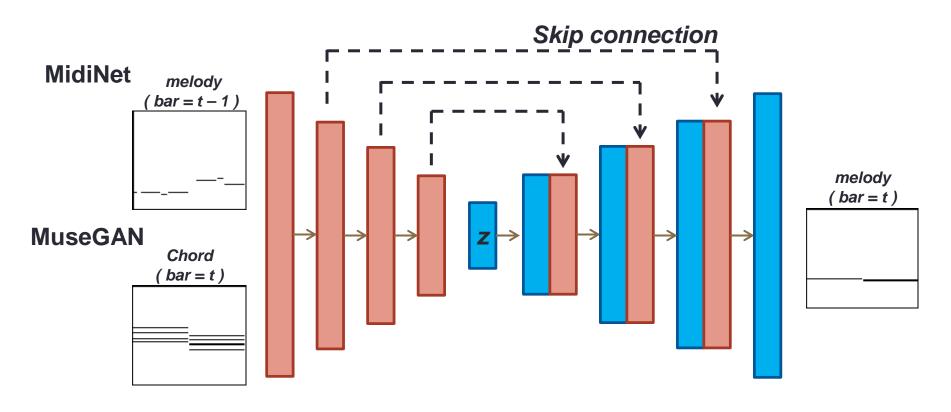
U-Net Encoder

Skip-connection: no information loss

MidiNet: previous bar

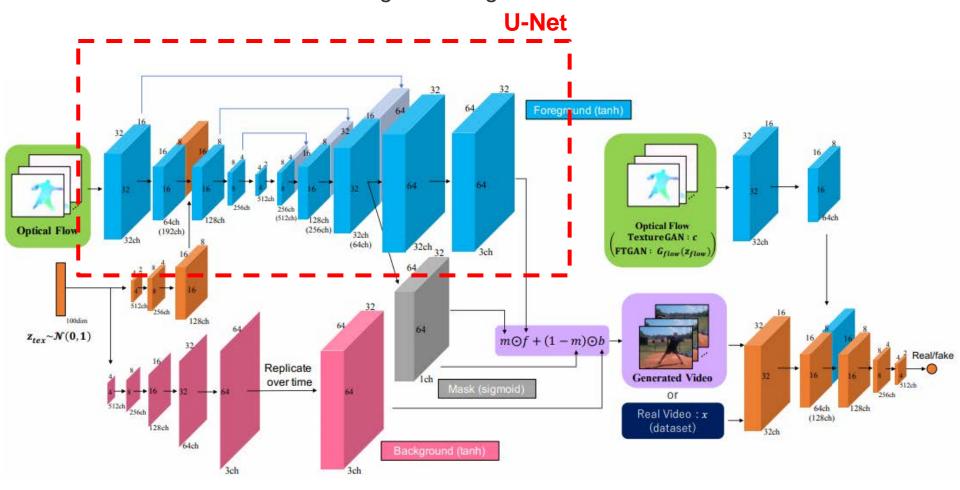
MuseGAN: accompanied track





U-Net Encoder

- FTGAN (video generation)
- Use conditional vector to guide the generation



^{*} Optical flow: a feature about motion

Tag

- Supervised GAN training
- Conditional generation
 - Given a class, generate images according to that
- Disentanglement
 - Try to acquire the attribute-invariant latent space or the controllability with limited labels (Ex: Gender)
 - Related Works:
 - DR-GAN
 - TD-GAN
 - Fader Network
 - StarGAN (CycleGAN)

















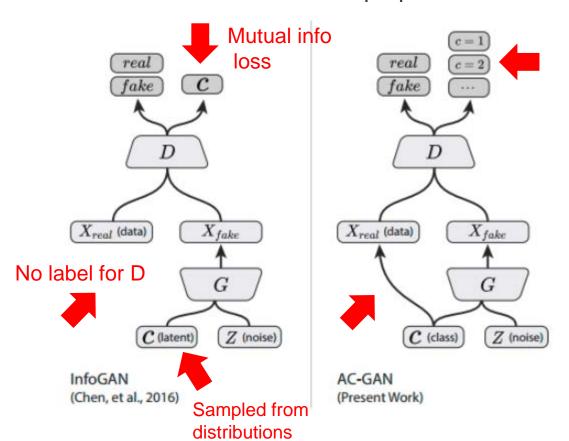


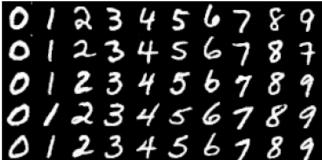
(male -> female) from Fader Network

Disentanglement

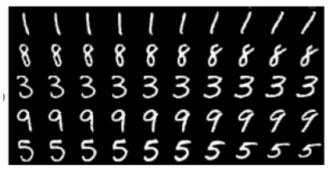
- Unsupervised?
 - infoGAN

add <u>mutual information loss</u> to encourage latent codes learn the most obvious properties





(a) Varying c_1 on InfoGAN (Digit type) (categorical)

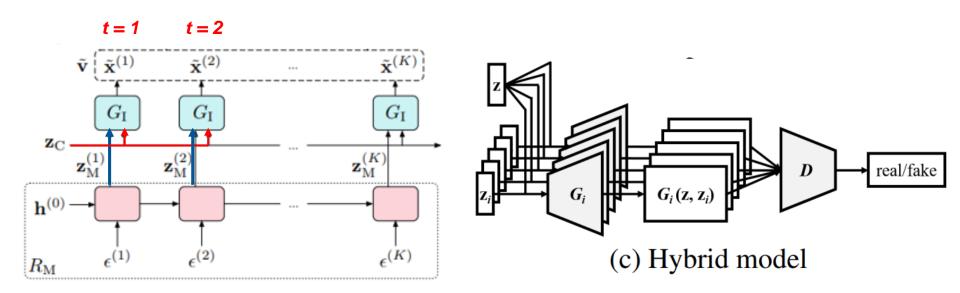


(c) Varying c_2 from -2 to 2 on InfoGAN (Rotation)

(continuous)

Disentanglement

- Unsupervised
 - mocoGAN & MuseGAN
 Design reasonable network architecture to encourage latent codes learn the variant and invariant properties
 - Both of works simply use 3DCNN in D



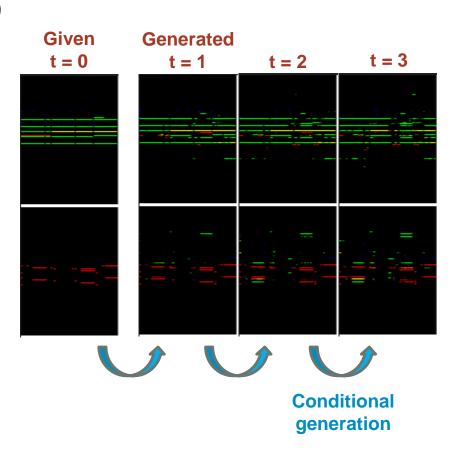
mocoGAN MuseGAN

Discussion

- Previous bar as condition (MidiNet)
 - For melody Good
 - For multi-track Failed!

- Reasons:
 - The source and target domain are the same
 - There are too many possible results

Finally, the network tries to copy and paste (AE, instead of U-Net)



^{*} MidiNet on multi-tracks

Video GANs

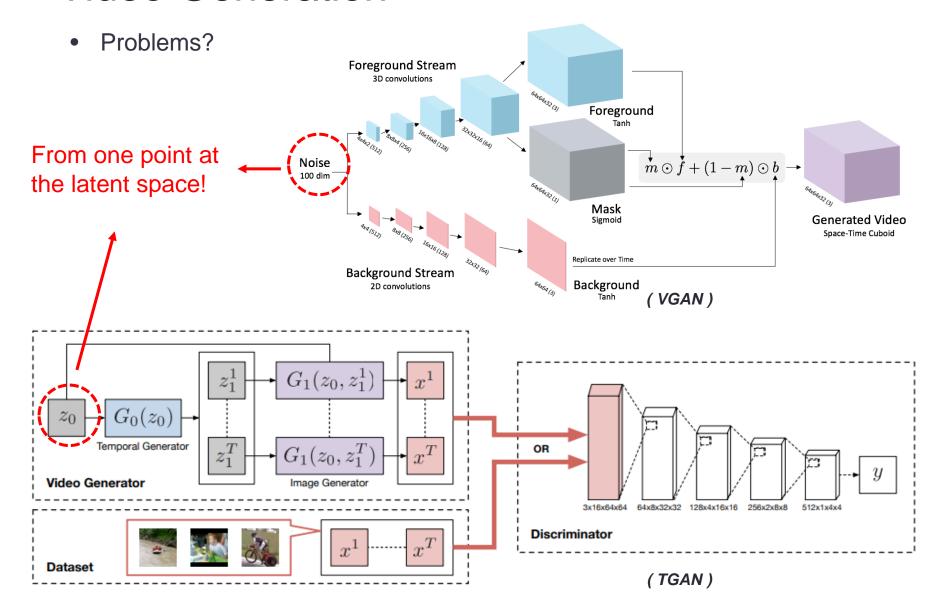
Related Works Discussion

- Early papers try to predict the next frame
 - MidiNet
- Recent works
 - VGAN
 - TGAN
 - mocoGAN
 - FTGAN
- It's too difficult to generate a sequence of images directly.
 - Decomposition the video

VGAN: foreground and backgrounf

mocoGAN: content and motion

 Using additional information to guide the generation FTGAN: optical flow



Sliding 3DCNN **Discriminator GIF** generation No scene transitions D_{T} 3DCNN discriminator only ensure every local block of frames is true S_T S_1 $\tilde{\mathbf{x}}^{(1)}$ $\tilde{\mathbf{x}}^{(2)}$ $\tilde{\mathbf{x}}^{(K)}$ Content invariant $G_{\rm I}$ G_{I} $G_{\rm I}$ \mathbf{z}_{C} – $\mathbf{z}_{\mathrm{M}}^{(2)}$ $\mathbf{z}_{\mathrm{M}}^{(K)}$ ${\bf h}^{(0)}$ $\epsilon^{(K)}$ $R_{\rm M}$ (MocoGAN)

conclusion

- GAN templates:
 - Chainer:
 - https://github.com/pfnet-research/chainer-gan-lib
 - https://github.com/pfnet-research/sngan_projection
 - Tensorflow:
 - https://github.com/carpedm20/DCGAN-tensorflow
 - https://github.com/wiseodd/generative-models
 - Pytorch:
 - https://github.com/eriklindernoren/PyTorch-GAN

END

Text GANs

Related Works Discussion