

Advanced Machine Learning Summer 2019

Part 17 – Generative Adversarial Networks 26.06.2019

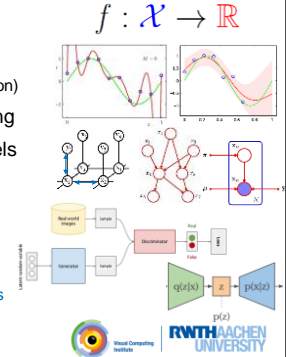
Prof. Dr. Bastian Leibe

RWTH Aachen University, Computer Vision Group
<http://www.vision.rwth-aachen.de>



Course Outline

- Regression Techniques
 - Linear Regression
 - Regularization (Ridge, Lasso)
 - Kernels (Kernel Ridge Regression)
- Deep Reinforcement Learning
- Probabilistic Graphical Models
 - Bayesian Networks
 - Markov Random Fields
 - Inference (exact & approximate)
 - Latent Variable Models
- Deep Generative Models
 - Generative Adversarial Networks
 - Variational Autoencoders



Visual Computing Institute | Prof. Dr. Bastian Leibe
Advanced Machine Learning
Part 17 – Generative Adversarial Networks



Topics of This Lecture

- Recap: Bayesian Mixture Models
- Generative Adversarial Networks (GANs)
 - Generative networks
 - GAN loss and training procedure
- Applications & Extensions
 - GANs for image generation
 - GANs for superresolution
 - Conditional GANs
- Problems of GANs
 - Problems during training
 - Conceptual problems
 - Extension: Wasserstein GANs

Visual Computing Institute | Prof. Dr. Bastian Leibe
Advanced Machine Learning
Part 17 – Generative Adversarial Networks



Recap: Bayesian Mixture Models

- Let's be Bayesian about mixture models
 - Place priors over our parameters
 - Again, introduce variable z_n as indicator which component data point x_n belongs to.

$$z_n | \pi \sim \text{Multinomial}(\pi)$$

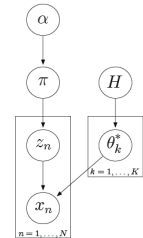
$$x_n | z_n = k, \mu, \Sigma \sim \mathcal{N}(\mu_k, \Sigma_k)$$

- Introduce **conjugate priors** over parameters

$$\pi \sim \text{Dirichlet}\left(\frac{\alpha}{K}, \dots, \frac{\alpha}{K}\right)$$

$$\mu_k, \Sigma_k \sim H = \mathcal{N} - \mathcal{IW}(0, s, d, \phi)$$

"Normal – Inverse Wishart"



Visual Computing Institute | Prof. Dr. Bastian Leibe
Advanced Machine Learning
Part 17 – Generative Adversarial Networks

Slide inspired by Yee Whye Teh



Recap: Bayesian Mixture Models

- Full Bayesian Treatment
 - Given a dataset, we are interested in the cluster assignments
$$p(\mathbf{Z} | \mathbf{X}) = \frac{p(\mathbf{X} | \mathbf{Z}) p(\mathbf{Z})}{\sum_{\mathbf{Z}} p(\mathbf{X} | \mathbf{Z}) p(\mathbf{Z})}$$

where the likelihood is obtained by marginalizing over the parameters θ

$$p(\mathbf{X} | \mathbf{Z}) = \int p(\mathbf{X} | \mathbf{Z}, \theta) p(\theta) d\theta$$

$$= \int \prod_{n=1}^N \prod_{k=1}^K p(x_n | z_{nk}, \theta_k) p(\theta_k | H) d\theta$$
- The posterior over assignments is intractable!
 - Denominator requires summing over all possible partitions of the data into K groups!
 - ⇒ Need efficient approximate inference methods to solve this...

Visual Computing Institute | Prof. Dr. Bastian Leibe
Advanced Machine Learning
Part 17 – Generative Adversarial Networks



Recap: Mixture Models with Dirichlet Priors

- Integrating out the mixing proportions π

$$p(\mathbf{z} | \alpha) = \int p(\mathbf{z} | \pi) p(\pi | \alpha) d\pi$$

$$= \frac{\Gamma(\alpha)}{\Gamma(N + \alpha)} \prod_{k=1}^K \frac{\Gamma(N_k + \alpha/K)}{\Gamma(\alpha/K)}$$
- Conditional probabilities
 - Examine the conditional of z_n given all other variables z_{-n}

$$p(z_{nk} = 1 | \mathbf{z}_{-n}, \alpha) = \frac{p(\mathbf{z}_{-n} | \alpha)}{p(\mathbf{z}_{-n, k} = 1, \mathbf{z}_{-n} | \alpha)}$$

$$= \frac{N_{-n, k} + \alpha/K}{N - 1 + \alpha}$$

$N_{-n, k} \stackrel{\text{def}}{=} \sum_{i=1, i \neq n}^N z_{ik}$
 - ⇒ The **more populous** a class is, the more likely it is to be joined!

Visual Computing Institute | Prof. Dr. Bastian Leibe
Advanced Machine Learning
Part 17 – Generative Adversarial Networks

Slide adapted from Zoubin Ghahramani



Recap: Infinite Dirichlet Mixture Models

- Conditional probabilities: Finite K

$$p(z_{nk} = 1 | \mathbf{z}_{-n}, \alpha) = \frac{N_{-n,k} + \alpha/K}{N - 1 + \alpha}, \quad N_{-n,k} \stackrel{\text{def}}{=} \sum_{i=1, i \neq n}^N z_{ik}$$

- Conditional probabilities: Infinite K

- Taking the limit as $K \rightarrow \infty$ yields the conditionals

$$p(z_{nk} = 1 | \mathbf{z}_{-n}, \alpha) = \begin{cases} \frac{N_{-n,k}}{N - 1 + \alpha} & \text{if } k \text{ represented} \\ \frac{\alpha}{N - 1 + \alpha} & \text{if all } k \text{ not represented} \end{cases}$$

- Left-over mass $\alpha \Rightarrow$ countably infinite number of indicator settings

7

Visual Computing Institute | Prof. Dr. Bastian Leibe
Advanced Machine Learning
Part 17 - Generative Adversarial Networks

Slide adapted from Zoubin Ghahramani



RWTH AACHEN
UNIVERSITY

Recap: Gibbs Sampling for Finite Mixtures

- We need approximate inference here

- Gibbs Sampling: Conditionals are simple to compute

$$p(\mathbf{z}_n = k | \text{others}) \propto \sum_{k=1}^K \pi_k \mathcal{N}(\mathbf{x}_n | \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)$$

$$\boldsymbol{\pi} | \mathbf{z} \sim \text{Dir}(N_1 + \alpha/K, \dots, N_K + \alpha/K)$$

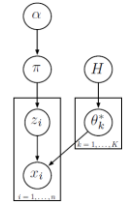
$$\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k | \text{others} \sim \mathcal{N} - \mathcal{IW}(v', s', d', \phi')$$

- However, this will be rather inefficient...

- In each iteration, algorithm can only change the assignment for individual data points.

- There are often groups of data points that are associated with high probability to the same component. \Rightarrow Unlikely that group is moved.

- Better performance by collapsed Gibbs sampling which integrates out the parameters $\boldsymbol{\pi}, \boldsymbol{\mu}, \boldsymbol{\Sigma}$



8

Visual Computing Institute | Prof. Dr. Bastian Leibe
Advanced Machine Learning
Part 17 - Generative Adversarial Networks

Slide adapted from Yee Whye Teh



RWTH AACHEN
UNIVERSITY

Image source: Yee Whye Teh

Recap: Collapsed Finite Bayesian Mixture

- More efficient algorithm

- Conjugate priors allow analytic integration of some parameters
- Resulting sampler operates on reduced space of cluster assignments (implicitly considers all possible cluster shapes)

- Procedure

- The model implies the factorization

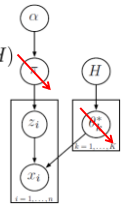
$$p(\mathbf{z}_n | \mathbf{z}_{-n}, \mathbf{x}, \alpha, H) \propto p(\mathbf{z}_n | \mathbf{z}_{-n}, \alpha) p(\mathbf{x}_n | \mathbf{z}_n, \mathbf{x}_{-n}, H)$$

- Derive

$$p(\mathbf{z} | \alpha) = \int p(\mathbf{z} | \boldsymbol{\pi}) p(\boldsymbol{\pi} | \alpha) d\boldsymbol{\pi} \quad \checkmark$$

$$p(\mathbf{x}_n | \mathbf{z}_n, H) = \int \sum_{k=1}^K z_{nk} p(\mathbf{x}_n | \boldsymbol{\theta}_k) p(\boldsymbol{\theta}_k | H) d\boldsymbol{\theta} \quad \checkmark$$

\Rightarrow Conjugate prior, Normal - Inverse Wishart



9

Visual Computing Institute | Prof. Dr. Bastian Leibe
Advanced Machine Learning
Part 17 - Generative Adversarial Networks

Slide adapted from Erik Sudderth



RWTH AACHEN
UNIVERSITY

Topics of This Lecture

- Recap: Bayesian Mixture Models

- Generative Adversarial Networks (GANs)

- Generative networks
- GAN loss and training procedure

- Applications & Extensions

- GANs for image generation
- GANs for superresolution
- Conditional GANs

- Problems of GANs

- Problems during training
- Conceptual problems
- Extension: Wasserstein GANs

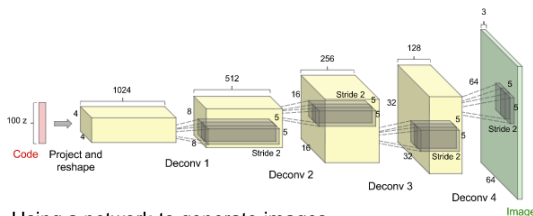
11

Visual Computing Institute | Prof. Dr. Bastian Leibe
Advanced Machine Learning
Part 17 - Generative Adversarial Networks



RWTH AACHEN
UNIVERSITY

Generative Networks



- Using a network to generate images

- Sampling from noise distribution
- Sequence of upsampling layers to generate an output image
- How can we train such a model to produce the desired output?

12

Visual Computing Institute | Prof. Dr. Bastian Leibe
Advanced Machine Learning
Part 17 - Generative Adversarial Networks

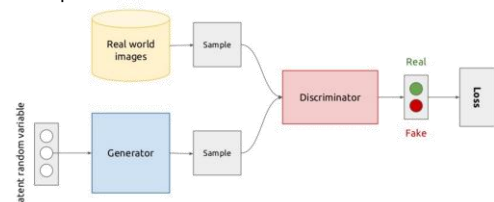


RWTH AACHEN
UNIVERSITY

Image from <https://blog.openai.com/generative-models>

Generative Adversarial Networks (GANs)

- Conceptual view



- Main idea

- Simultaneously train an image generator G and a discriminator D .
- Interpreted as a two-player game

13

Visual Computing Institute | Prof. Dr. Bastian Leibe
Advanced Machine Learning
Part 17 - Generative Adversarial Networks

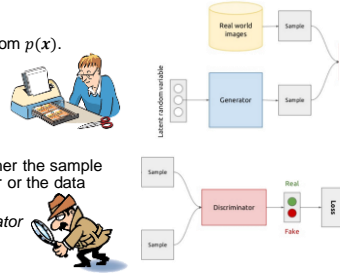


RWTH AACHEN
UNIVERSITY

Image credit: Kevin McGuinness

Two-Player Game

- **Generator**
 - Tries to draw samples from $p(x)$.
 - Analogy: *counterfeiter*
- **Discriminator**
 - Tries to determine whether the sample came from the generator or the data distribution.
 - Analogy: *police investigator*
- Both generator and discriminator are deep networks
 - We can train them with backprop.



14

Visual Computing Institute | Prof. Dr. Bastian Leibe
Advanced Machine Learning
Part 17 - Generative Adversarial Networks

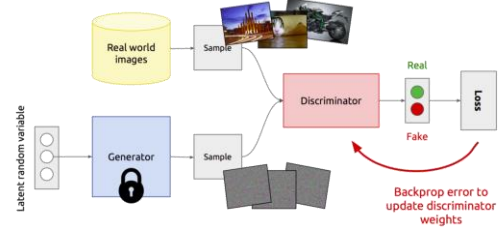


RWTH AACHEN
UNIVERSITY

Image sources: www.bundesbank.de, weclipart.com, Kevin McGuinness

Training the Discriminator

- **Procedure**
 - Fix generator weights
 - Train discriminator to distinguish between real and generated images



15

Visual Computing Institute | Prof. Dr. Bastian Leibe
Advanced Machine Learning
Part 17 - Generative Adversarial Networks

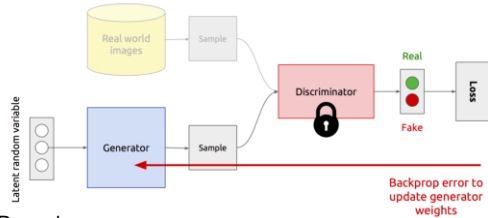


RWTH AACHEN
UNIVERSITY

Image credit: Kevin McGuinness

Training the Generator

- **Procedure**
 - Fix discriminator weights
 - Sample from generator
 - Backprop through discriminator to update generator weights



16

Visual Computing Institute | Prof. Dr. Bastian Leibe
Advanced Machine Learning
Part 17 - Generative Adversarial Networks



RWTH AACHEN
UNIVERSITY

Image credit: Kevin McGuinness

Formalizing This Procedure

- This corresponds to a two-player minimax game:

$$\min_G \max_D V(D, G) = \mathbb{E}_{x \sim p_{data}(x)} [\log D(x)] + \mathbb{E}_{z \sim p_z(z)} [\log (1 - D(G(z)))]$$
- **Explanation**
 - Train D to maximize the probability of assigning the correct label to both training examples and samples from G .
 - Simultaneously train G to minimize $\log (1 - D(G(z)))$.
- The Nash equilibrium of this game is achieved at
 - $p_g(x) = p_{data}(x) \quad \forall x$
 - $D(x) = \frac{1}{2} \quad \forall x$

17

Visual Computing Institute | Prof. Dr. Bastian Leibe
Advanced Machine Learning
Part 17 - Generative Adversarial Networks



RWTH AACHEN
UNIVERSITY

GAN Algorithm

Algorithm 1 Minibatch stochastic gradient descent training of generative adversarial nets. The number of steps to apply to the discriminator, k , is a hyperparameter. We used $k = 1$, the least expensive option, in our experiments.

for number of training iterations do

for k steps do

- Sample minibatch of m noise samples $\{z^{(1)}, \dots, z^{(m)}\}$ from noise prior $p_g(z)$.
- Sample minibatch of m examples $\{x^{(1)}, \dots, x^{(m)}\}$ from data generating distribution $p_{data}(x)$.
- Update the discriminator by ascending its stochastic gradient:

$$\nabla_{\theta_D} \frac{1}{m} \sum_{i=1}^m [\log D(x^{(i)}) + \log (1 - D(G(z^{(i)})))] \quad \text{Discriminator updates}$$

end for

- Sample minibatch of m noise samples $\{z^{(1)}, \dots, z^{(m)}\}$ from noise prior $p_g(z)$.
- Update the generator by descending its stochastic gradient:

$$\nabla_{\theta_G} \frac{1}{m} \sum_{i=1}^m \log (1 - D(G(z^{(i)}))) \quad \text{Generator updates}$$

end for

The gradient-based updates can use any standard gradient-based learning rule. We used momentum in our experiments.

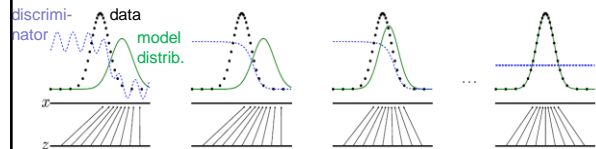
18

Visual Computing Institute | Prof. Dr. Bastian Leibe
Advanced Machine Learning
Part 17 - Generative Adversarial Networks



RWTH AACHEN
UNIVERSITY

Intuition



- **Behavior near convergence**
 - In the inner loop, D is trained to discriminate samples from data.
 - Gradient of D guides G to flow to regions that are more likely to be classified as data.
 - After several steps of training, G and D will reach a point at which they cannot further improve, because $p_g = p_{data}$.
 - Now, the discriminator is unable to differentiate between the two distributions, i.e., $D(x) = 0.5$.

19

Visual Computing Institute | Prof. Dr. Bastian Leibe
Advanced Machine Learning
Part 17 - Generative Adversarial Networks



RWTH AACHEN
UNIVERSITY

Topics of This Lecture

- Recap: Bayesian Mixture Models
- Generative Adversarial Networks (GANs)
 - Generative networks
 - GAN loss and training procedure
- Applications & Extensions
 - GANs for image generation
 - GANs for superresolution
 - Conditional GANs
- Problems of GANs
 - Problems during training
 - Conceptual problems
 - Extension: Wasserstein GANs

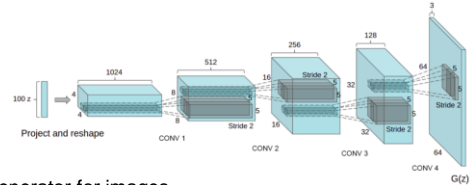
20

Visual Computing Institute | Prof. Dr. Bastian Leibe
Advanced Machine Learning
Part 17 – Generative Adversarial Networks



RWTH AACHEN
UNIVERSITY

Example: Deep Convolutional GAN (DCGAN)



- Generator for images
 - Remove fully-connected layers
 - Upsampling with **fractional strided convolutions**
 - **Batch normalization** after each layer (important!)
 - Use **ReLU** in generator for hidden layers, tanh for output layer
 - Use **Leaky ReLU** in the discriminator for all layers

21

Visual Computing Institute | Prof. Dr. Bastian Leibe
Advanced Machine Learning
Part 17 – Generative Adversarial Networks



RWTH AACHEN
UNIVERSITY

Image credit: Alec Radford et al.

Example Application: Image Generation



- Generating bedroom images
 - Each sample is generated from a sampled random number

22

Visual Computing Institute | Prof. Dr. Bastian Leibe
Advanced Machine Learning
Part 17 – Generative Adversarial Networks



RWTH AACHEN
UNIVERSITY

Image credit: Alec Radford et al.

Example Application: Image Generation



- Interpolating between the random points in latent space...

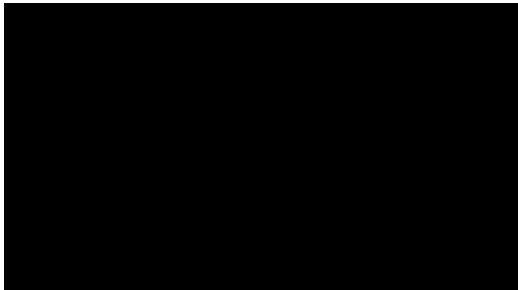
23

Visual Computing Institute | Prof. Dr. Bastian Leibe
Advanced Machine Learning
Part 17 – Generative Adversarial Networks



RWTH AACHEN
UNIVERSITY

Interpolation between Face Images



Karras et al., "Progressive growing of GANs for improved quality, stability, and variation", ICLR'18

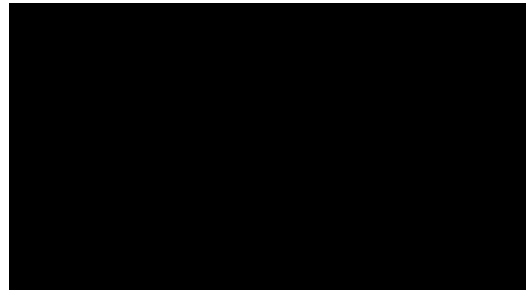
24

Visual Computing Institute | Prof. Dr. Bastian Leibe
Advanced Machine Learning
Part 17 – Generative Adversarial Networks



RWTH AACHEN
UNIVERSITY

Interpolation between Arbitrary Images



Karras et al., "Progressive growing of GANs for improved quality, stability, and variation", ICLR'18

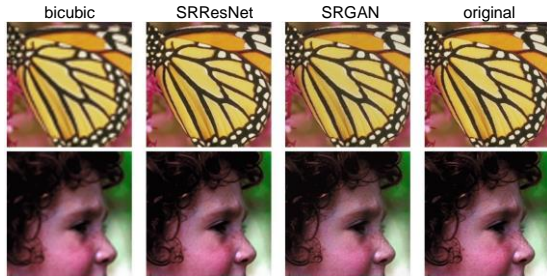
25

Visual Computing Institute | Prof. Dr. Bastian Leibe
Advanced Machine Learning
Part 17 – Generative Adversarial Networks



RWTH AACHEN
UNIVERSITY

Example Application: Super-Resolution (SRGAN)

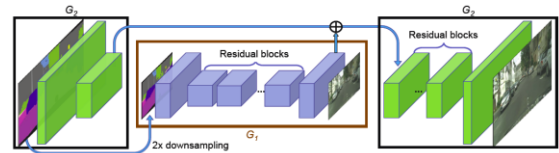


26 Visual Computing Institute | Prof. Dr. Bastian Leibe
Advanced Machine Learning
Part 17 – Generative Adversarial Networks



Image credit: C. Ledig et al.

Extension: Conditional GANs



- Idea
 - Condition the latent space representation on an input image
 - Used to create the pix2pix network

P. Isola, J.-Y. Zhu, T. Zhou, and A. A. Efros. Image-to-image translation with conditional adversarial networks. CVPR 2017.

27 Visual Computing Institute | Prof. Dr. Bastian Leibe
Advanced Machine Learning
Part 17 – Generative Adversarial Networks



Extension: Conditional GANs



T.-C. Wang, M.-Y. Liu, J.-Y. Zhu, A. Tao, J. Kautz, B. Catanzaro, High-Resolution Image Synthesis and Semantic Manipulation with Conditional GANs, CVPR 2018.

28 Visual Computing Institute | Prof. Dr. Bastian Leibe
Advanced Machine Learning
Part 17 – Generative Adversarial Networks



Artist Project: edges2cats [Christopher Hesse]



29 Visual Computing Institute | Prof. Dr. Bastian Leibe
Advanced Machine Learning
Part 17 – Generative Adversarial Networks



Slide credit: Alisa Efros

Topics of This Lecture

- Recap: Bayesian Mixture Models
- Generative Adversarial Networks (GANs)
 - Generative networks
 - GAN loss and training procedure
- Applications & Extensions
 - GANs for image generation
 - GANs for superresolution
 - Conditional GANs
- Problems of GANs
 - Problems during training
 - Conceptual problems
 - Extension: Wasserstein GANs

30 Visual Computing Institute | Prof. Dr. Bastian Leibe
Advanced Machine Learning
Part 17 – Generative Adversarial Networks



What Can Possibly Go Wrong? Problems with GANs

- Problem 1: Vanishing gradients
 - When the discriminator is perfect, the loss function falls to zero.
 - No gradient to update the loss during learning iterations.
- Dilemma: *Walking a fine line...*
 - Discriminator behaves badly \Rightarrow generator does not have accurate feedback
 - Discriminator does a great job \Rightarrow gradient of the loss drops close to zero

31 Visual Computing Institute | Prof. Dr. Bastian Leibe
Advanced Machine Learning
Part 17 – Generative Adversarial Networks

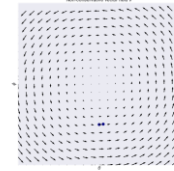


What Can Possibly Go Wrong? Problems with GANs



- Problem 2: Mode collapse
 - Even though the generator might be able to trick the discriminator, it may fail to represent the complex real-world data distribution.
 - Training gets stuck in a small space with little variety

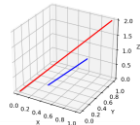
What Can Possibly Go Wrong? Problems with GANs



- Problem 3: Non-convergence
 - GANs involve two players
 - Each model updates its cost independently
 - This means we are performing simultaneous gradient descent
 - Problem: might not converge to Nash equilibrium

Image source: Ferenc Huszar, Ilija Weng

What Can Possibly Go Wrong? Problems with GANs



- Problem 4: Low-dimensional support
 - Both p_{data} and p_g lie on low-dimensional manifolds.
 - Those manifolds most likely do not intersect
 - The Jensen divergence implicitly optimized in GANs cannot deal with this well.
 - Wasserstein GANs fix this by introducing a different loss function.

Image source: Ferenc Huszar, Ilija Weng

Summary

- Advantages
 - GANs can be trained with backpropagation
 - Generated images are sharper than from VAEs
 - Robust to overfitting, since generator never sees the training data
 - Fast process: single forward pass generates a single sample
- Disadvantages
 - GANs are well known for being delicate and unstable
 - Problems with non-convergence
 - Problems with mode collapse
- Extensions
 - Wasserstein GANs fix several major problems in the GAN formulation
 - Energy-based GANs allow general loss functions

2017: Explosion of GANs

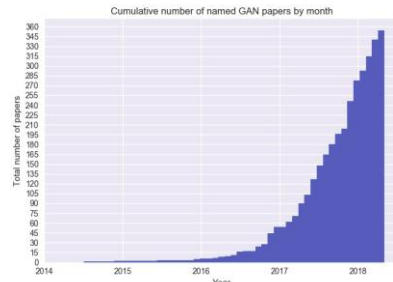
• "The GAN Zoo"

- GAN - Generative Adversarial Networks
- 3D-GAN - Learning a Probabilistic Latent Space of Object Shapes via 3D Generative-Adversarial Modeling
- aCGAN - Face Aging with Conditional Generative Adversarial Networks
- AC-GAN - Conditional Image Synthesis With Auxiliary Classifier GANs
- AGGAN - Adversarial Gradient Boosting Generative Models
- ARGAN - Learning Image Resizing by Adversarial Based Generative Adversarial Nets
- ARS-GAN - Annotated Style Transfer for Image Super-Resolution
- AU-CGAN - Learning to Generate Images of Outdoor Scenes from Attributes and Semantic Layouts
- AUL - Anomaly Unlearned Instance
- AM-GAN - Generative Adversarial Nets with Labeled Data by Activation Maximization
- ANGAN - Unsupervised Anomaly Detection with Generative Adversarial Networks to Guide Marker Discovery
- aPGAN - Anomaly Detection with Conditional GANs
- B-GAN - B-GAN: Unified Framework of Generative Adversarial Networks
- Boundary-GAN - Deep and Hierarchical Inside Models
- BEGAN - Boundary Equilibrium Generative Adversarial Networks
- BGAN - Adversarial Feature Learning
- BE-GAN - Boundary-Defining Generative Adversarial Networks
- CGAN - Conditional Generative Adversarial Nets
- CAGAN - Conditional Stylizing via High Energy Particle Beams in Multi-Layer Electrostatic Colorizers with Generative Adversarial Networks
- CGGAN - Semi-Supervised Learning with Context-Conditional Generative Adversarial Networks
- CGGAN - Semi-Supervised Learning with Context-Conditional Generative Adversarial Networks
- CGAN - Unsupervised and Semi-Supervised Learning with Conditional Generative Adversarial Networks
- CGAN - Coupled Generative Adversarial Networks
- Context-RNN-GAN - Contextual RNN-GANs for Abstract Reasoning (Region-Generative)
- D-IRMGAN - D-IRMGAN: Continuous-Parameter Neural Networks with Attentional Learning
- DCGAN - Hopfield Neural Machine Translation with Generative Adversarial Networks
- DRG-GAN - DRG-GAN: Fine-Grained Image Generation through Appearance Training
- DQuGAN - Unsupervised Image-to-Image Translation using Dual-Generative Adversarial Networks
- DTP - Unsupervised Cross-Domain Image Generation
- DCGAN - Unsupervised Representation Learning with Dual-Generative Adversarial Networks
- DQuGAN - Learning to Discover Cross-Domain Relations with Generative Adversarial Networks
- DCGAN - Unsupervised Representation Learning with Dual-Generative Adversarial Networks
- DQuGAN - DualGAN: Unsupervised Cross-Learning for Image-to-Image Translation
- DSGAN - Deep Style Generative Adversarial Networks
- F-GAN - F-GAN: Training Generative Neural Networks using Variational Divergence Minimization
- F-GAN - Towards Language-First Image Translation in the Wild
- GANGAN - Learning What and Where to Draw
- GANGAN - Contextual Learning: Object Transfer and Attribute Subspace from Unpaired Data
- Generative GAN - Invariant GAN
- GANGAN - StyleGAN: Generative Adversarial Networks with StyleTransfer/StyleGAN Training
- GP-GAN - GP-GAN: Towards Realistic High-Resolution Image Synthesis
- GAN - Generative Neural Representation on the Natural Image manifold
- WGAN - Wasserstein GAN with Lipschitz Adversarial Networks
- GAN - Generative Neural Representation on the Natural Image manifold
- GAN - Inverse Conditional GANs for Image Editing
- GCGAN - Image-to-Image Synthesis using Conditional Generative Adversarial Networks
- GCGAN - Image-to-Image Synthesis using Conditional Generative Adversarial Networks
- Improved GAN - Improved Techniques for Training GANs
- HGAN - Hybrid Hierarchical Representation Learning by Information Maximizing Generative Adversarial Nets
- LSGAN - Learning Particle Physics to Generate Location-Aware Generative Adversarial Networks for Physics Experiments
- LFGAN - Deep Generative Image Models using a Latent Pyramid of Attentional Networks

<https://github.com/hindupuravinash/the-gan-zoo>

Slide credit: FoPaLi

Interest in GANs Is Still Growing...



<https://github.com/hindupuravinash/the-gan-zoo>

References

- Original GAN
 - I. J. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, Y. Bengio, [Generative Adversarial Nets](#), NIPS, 2014.
 - A. Radford, L. Metz, S. Chintala, [Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks](#), arXiv 1511.06434, 2015.
- GAN Extensions
 - J. Zhao, M. Mathieu, Y. LeCun, [Energy-based Generative Adversarial Networks](#), arXiv 1506.03365, 2015.
 - M. Arjovsky, S. Chintala, L. Bottou, [Wasserstein GAN](#), arXiv 1701.07875, 2017.
- Evaluations
 - M. Lucic, K. Kurach, M. Michalski, S. Gelly, O. Bousquet, [Are GANs Created Equal? A Large-Scale Study](#), arXiv 1711.10337, 2017.

