AC-GAN : Auxiliary Classifier GANs

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Data **M**ining and **Q**uality **A**nalytics

발표자 소개

- 신욱수 (Wooksoo Shin)
  - Data Mining & Quality Analytics Lab
  - 박사과정 (2019.03 ~ present)

- Research Interest
  - Machine Learning Algorithm including Image Classification
  - Complexity Analysis
  - Scheduling & Allocation Algorithm

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- Previous talk
  - DMQA Seminar : Mixup and Application (https://youtu.be/-pdrOYcgSrE)
  - NVIDIA GTC 21, High-performance/High-efficiency AI Model Training Cluster based on Kubernetes
    - https://www.nvidia.com/en-us/on-demand/session/gtcfall21-a31311/

AC-GAN

Conditional Image Synthesis with Auxiliary Classifier GANs

- ICML 2017

Conditional Image Synthesis with Auxiliary Classifier GANs

Augustus Odena [1] **Christopher Olah** [1] **Jonathon Shlens** [1]

Abstract

In this paper we introduce new methods for the improved training of generative adversarial networks (GANs) for image synthesis. We construct a variant of GANs employing label conditioning that results in 128×128 resolution image samples exhibiting global coherence. We expand on previous work for image quality assessment to provide two new analyses for assessing the discriminability and diversity of samples from class-conditional image synthesis models. These analyses demonstrate that high resolution samples provide class information not present in low resolution samples. Across 1000 ImageNet classes, 128×128 samples are more than twice as discriminable as artificially resized 32×32 samples. In addition, 84.7% of the classes have samples exhibiting diversity comparable to real ImageNet data.

[1]Google Brain. Correspondence to: Augustus Odena <augustusodena@google.com>.

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옛날 이야기

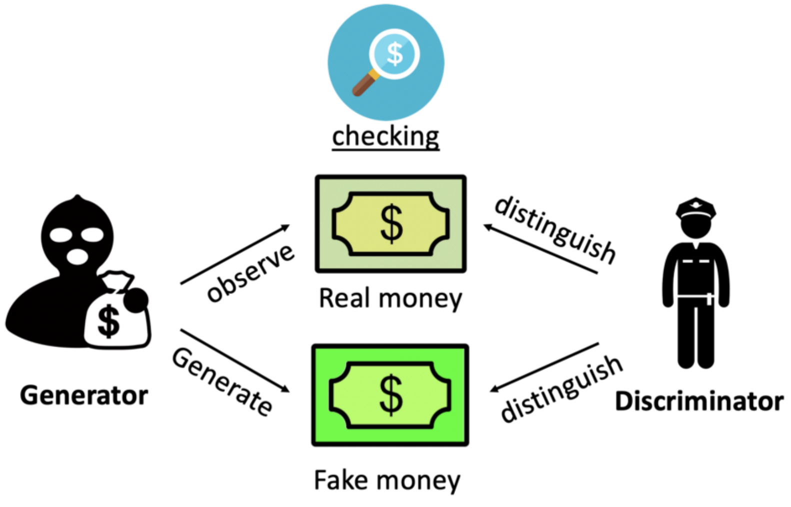
楚人有鬻盾與矛者，
譽之曰：「吾盾之堅，物莫能陷之。」
以譽其矛曰：「吾矛之利，於物無不陷也。」
或曰：「以子之矛陷子之盾，何如？」
其人弗能應也。
夫不可陷之盾與無不陷之矛，不可同世而立。

초나라 사람 중에 방패와 창을 파는 자가 있었다.
방패를 칭찬하며 말하였다. "내 방패는 견고해서 어떤 물건으로도 뚫을 수 없다."
그리고서는 창을 칭찬하며 말하였다. "내 창은 날카로워서 뚫지 못하는 물건이 없다."
누군가가 말하였다. "당신의 창으로 당신의 방패를 뚫으면 어떻게 되는가?"
그 사람은 대답할 수 없었다.
무릇 뚫을 수 없는 방패와 뚫지 못하는 물건이 없는 창은 같은 세상에 양립할 수 없는 것이다.

고려대학교 KOREA UNIVERSITY DMQA

Generator vs Discriminator

1. 띠형 홀로그램
2. 입체형 부분노출은선
3. 가로확대형 기번호
4. 색변환잉크
5. 숨은그림
6. 돌출은화
7. 요판잠상
8. 숨은은선
9. 볼록인쇄
10. 앞뒷면맞춤
11. 엔드리스 무늬
12. 무지개인쇄
13. 형광잉크
14. 형광색사
15. 필터형잠상
16. 미세문자



Adversarial Relationship

Source : 한국은행 https://www.bok.or.kr/portal/main/contents.do?menuNo=200371

GAN

Generative Adversarial Nets

Generative Adversarial Nets

Ian J. Goodfellow,[∗] Jean Pouget-Abadie,[†] Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair,[‡] Aaron Courville, Yoshua Bengio[§]
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Abstract

We propose a new framework for estimating generative models via an adversarial process, in which we simultaneously train two models: a generative model G that captures the data distribution, and a discriminative model D that estimates the probability that a sample came from the training data rather than G. The training procedure for G is to maximize the probability of D making a mistake. This framework corresponds to a minimax two-player game. In the space of arbitrary functions G and D, a unique solution exists, with G recovering the training data distribution and D equal to $\frac{1}{2}$ everywhere. In the case where G and D are defined by multilayer perceptrons, the entire system can be trained with backpropagation. There is no need for any Markov chains or unrolled approximate inference networks during either training or generation of samples. Experiments demonstrate the potential of the framework through qualitative and quantitative evaluation of the generated samples.

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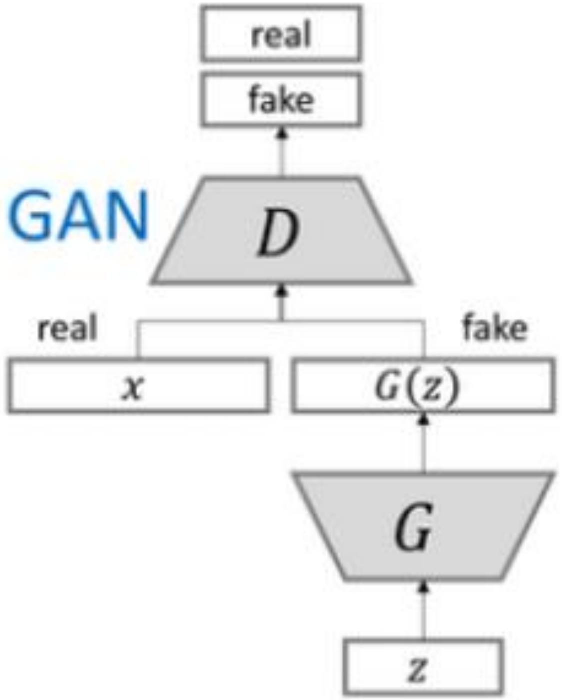
GAN : Network & Objective Function



$$\min_{G} \max_{D} V(D,G) = \mathbb{E}_{x \sim Pdata(x)}[log D(x)] + \mathbb{E}_{z \sim Pz(z)}[\log(1 - D(G(z)))]$$

C-GAN : Conditional GAN

Conditional Generative Adversarial Nets

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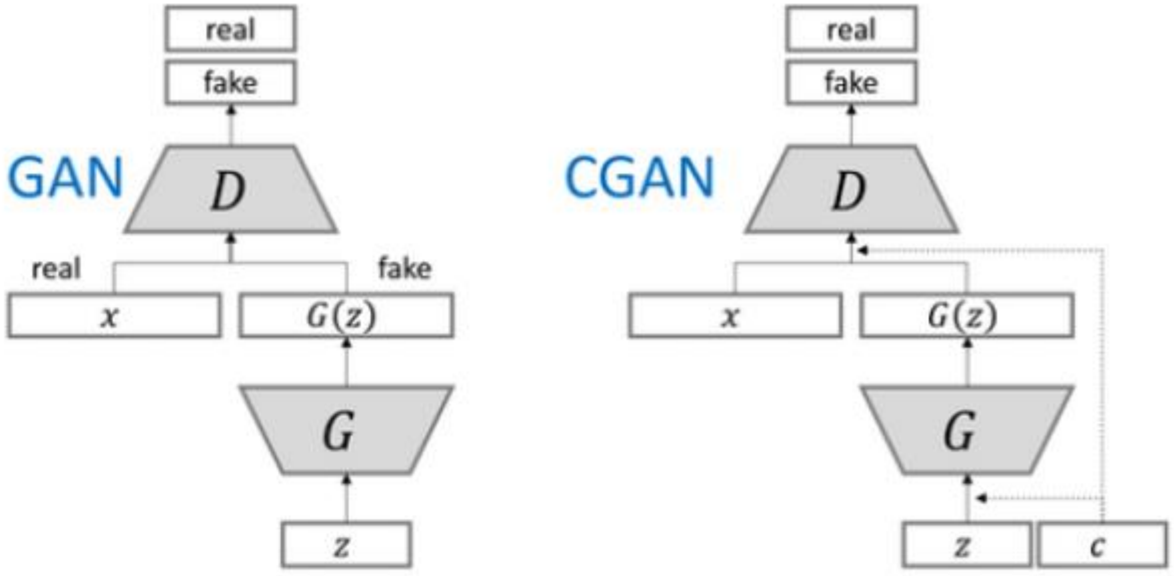
Abstract

Generative Adversarial Nets [8] were recently introduced as a novel way to train generative models. In this work we introduce the conditional version of generative adversarial nets, which can be constructed by simply feeding the data, y, we wish to condition on to both the generator and discriminator. We show that this model can generate MNIST digits conditioned on class labels. We also illustrate how this model could be used to learn a multi-modal model, and provide preliminary examples of an application to image tagging in which we demonstrate how this approach can generate descriptive tags which are not part of training labels.



GAN $min_G max_D V(D,G) = \mathbb{E}_{x\sim p_{data}(x)}[logD(x)] + \mathbb{E}_{x\sim p_z(z)}[log(1-D(G(z)))]$

CGAN $min_G max_D V(D,G) = \mathbb{E}_{x\sim p_{data}(x)}[logD(x|y)] + \mathbb{E}_{x\sim p_z(z)}[log(1-D(G(z|y)))]$

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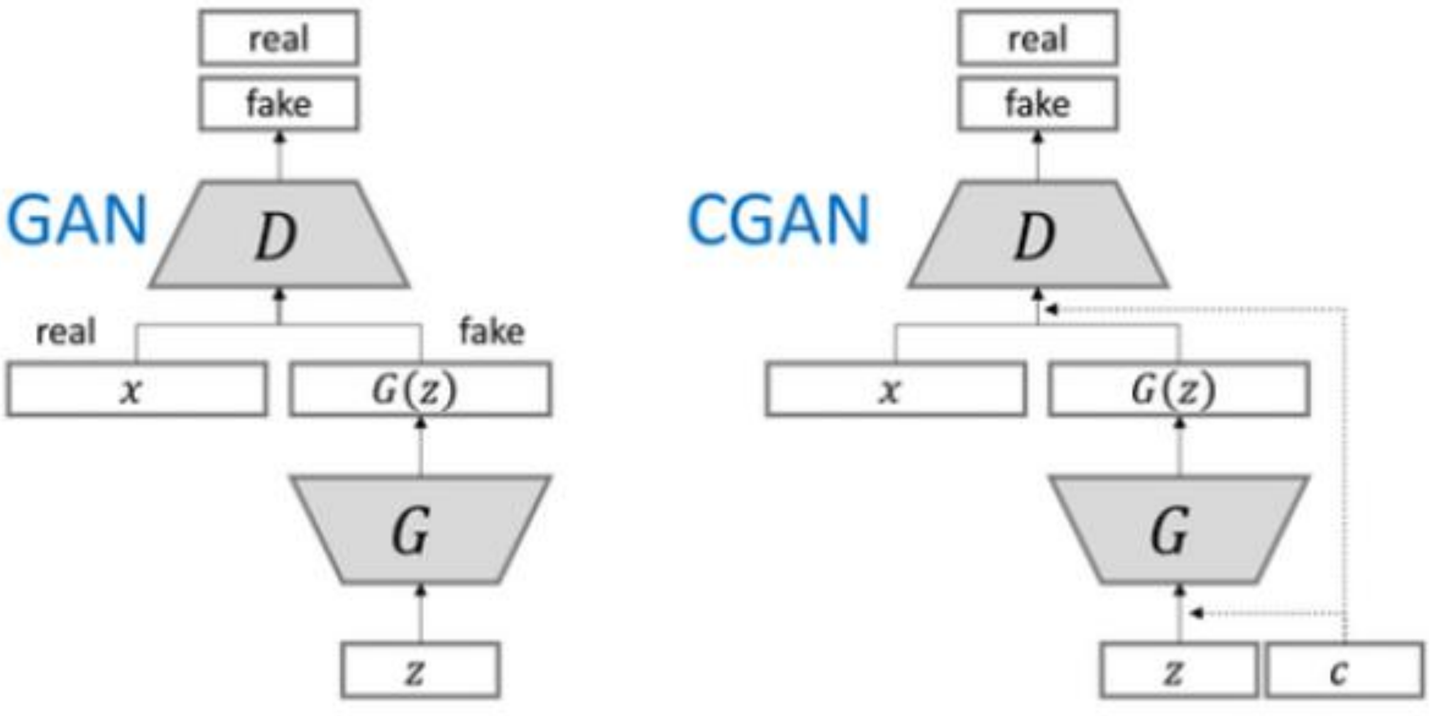
GAN architectures



AC-GAN : objective function

log-likelihood of the correct source : L_S

$$L_S = E[\log P(S = real|X_{real})] + E[\log P(S = fake|X_{fake})]$$

log-likelihood of the correct class : L_C

$$L_C = E[\log P(C = c|X_{real})] + E[\log P(C = c|X_{fake})]$$

D is trained to maximize $\boldsymbol{L_C + L_S}$

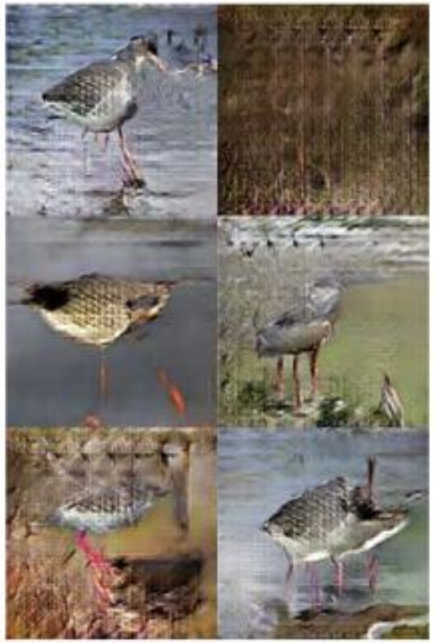
G is trained to maximize $\boldsymbol{L_C - L_S}$

AC-GAN result

monarch butterfly

goldfinch

daisy

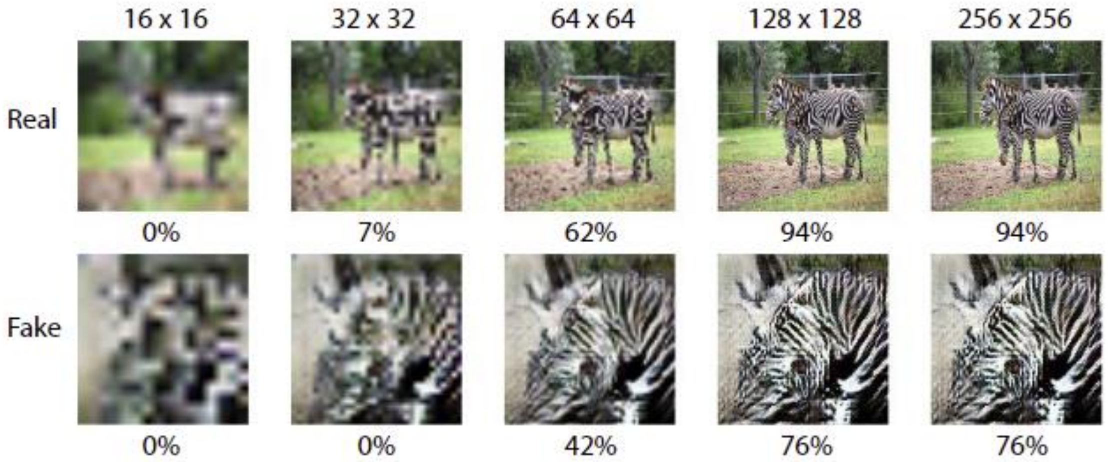


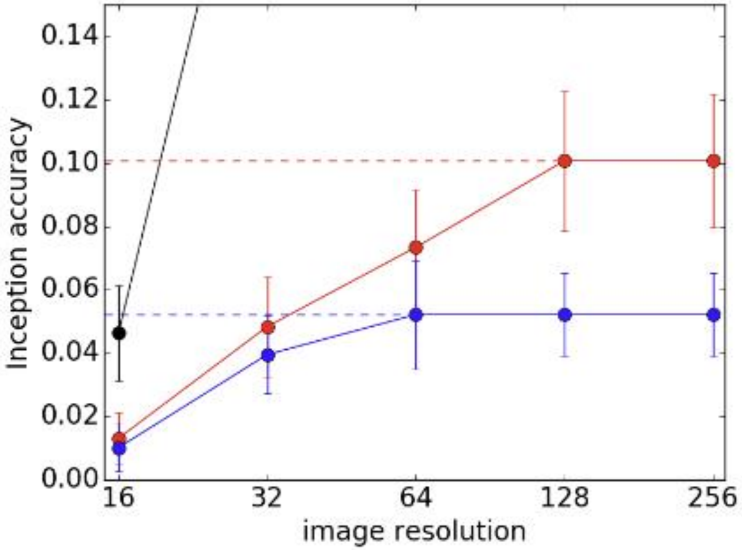
redshank

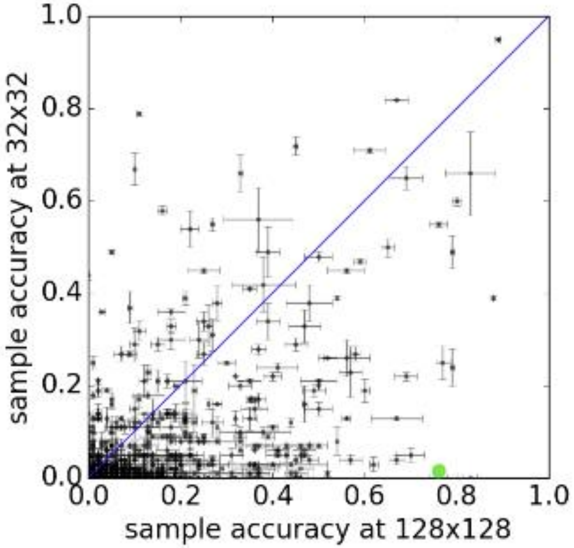
grey whale

AC-GAN : Discriminator

이미지 해상도를 크게할 수록 학습도 더 잘 된다.

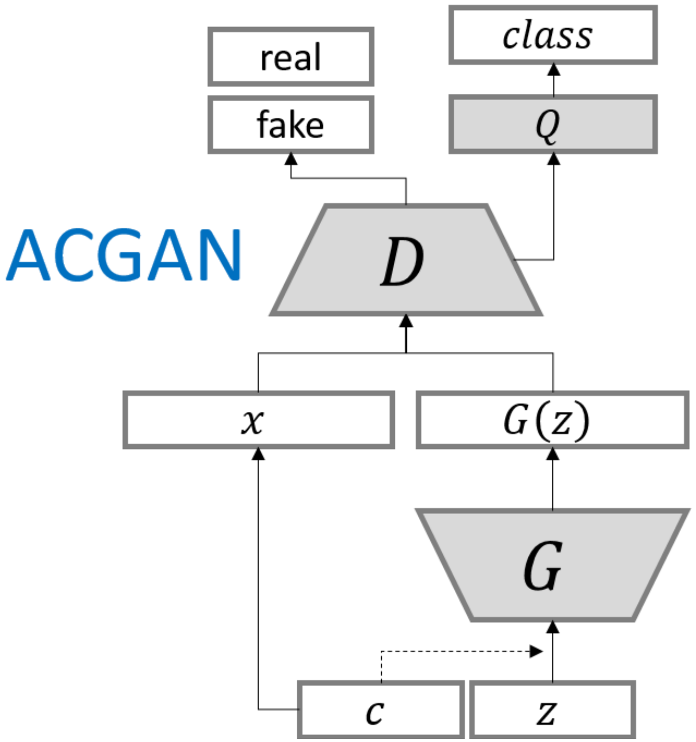






AC-GAN Summary

일반 GAN에 비해 Discriminator가 클래스 분류할 수 있는 기능을 가짐



$$L_S = E[logP(S = real|X_{real})] + E[logP(S = fake|X_{fake})]$$

$$L_C = E[logP(C = c|X_{real})] + E[logP(C = c|X_{fake})]$$

D is trained to maximize $L_C + L_S$

G is trained to maximize $L_C - L_S$

감사합니다.