

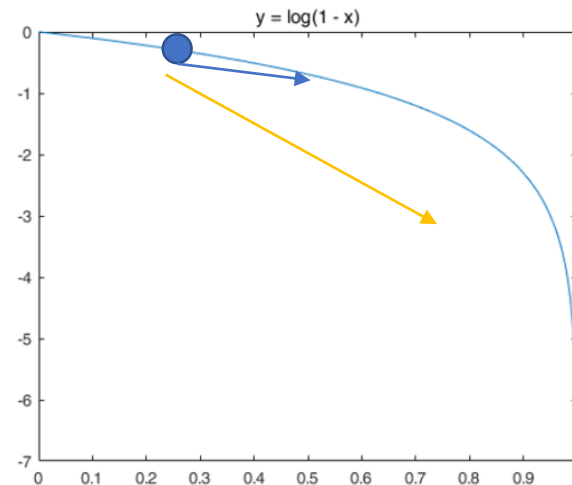
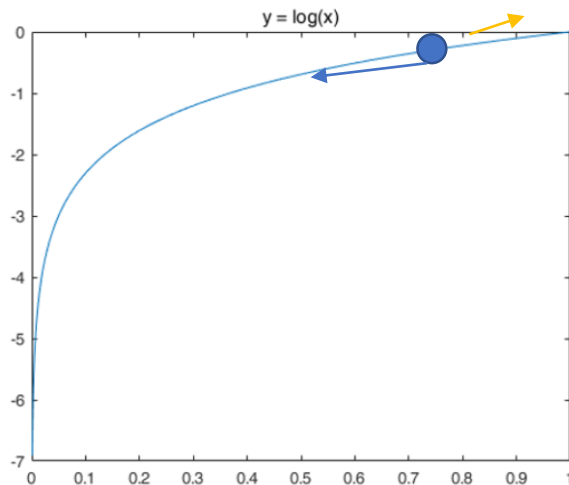
Unrolled gan

using the optimal discriminator(in the generator's objectives) impossible

- k steps of optimizing D and one step of optimizing G
- D: near optimal solution
- G: change slowly enough

x: data variable , z: noise variable, G(z): fake data

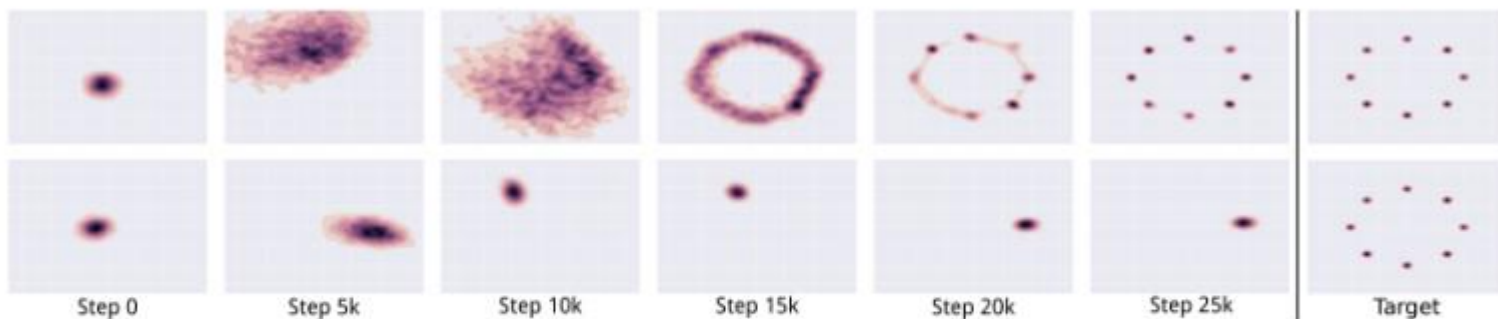
$$\min_G \max_D V(D, G) = \mathbb{E}_{\mathbf{x} \sim p_{\text{data}}(\mathbf{x})} [\log D(\mathbf{x})] + \mathbb{E}_{\mathbf{z} \sim p_{\mathbf{z}}(\mathbf{z})} [\log(1 - D(G(\mathbf{z})))].$$



Unstability of gan

- Mode collapsing or dropping (generator)
- Generator and discriminator oscillating during training
- No learning when the power between generator and discriminator is unbalanced.

Mode collapsing



Unrolled GAN(위) vs. standard GAN(아래)

Neural network의 입장에서는 이러한 **minimax problem**과 아래와 같은 **maximin problem**이 구별이 되지 않습니다:

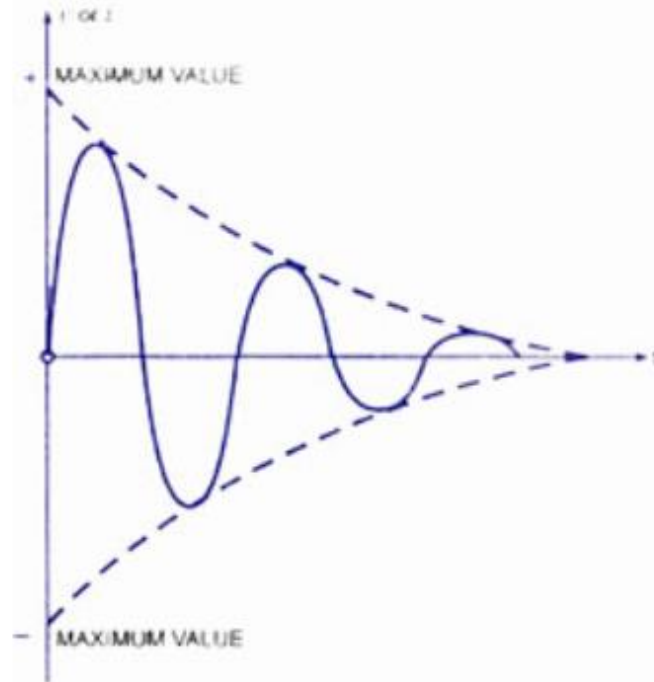
$$G^* = \min_G \max_D V(G, D).$$

$$G^* = \max_D \min_G V(G, D).$$

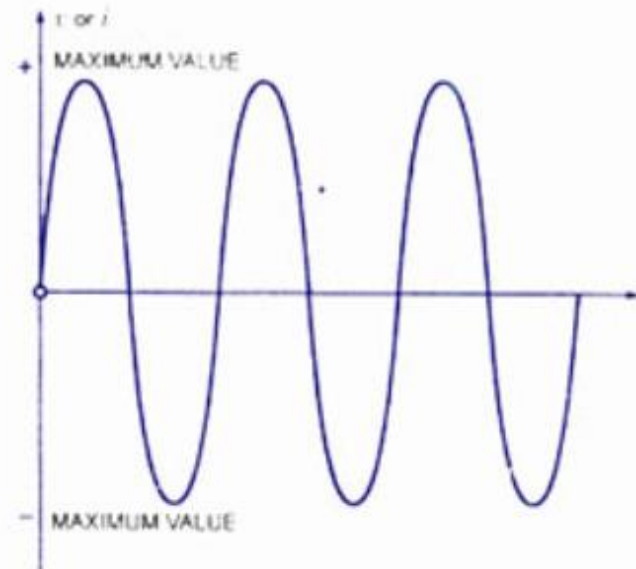


G 에 대한 minimization 문제가 먼저 있기 때문에 generator의 입장에서는 현재 고정되어있는 discriminator (non-optimal)가 가장 헛갈려 할 수 있는 sample 하나만 즉, value V 를 가장 최소화할 수 있는 mode 하나만을 내보내면 그만입니다.

Undamped oscillation



(a) Damped Oscillations

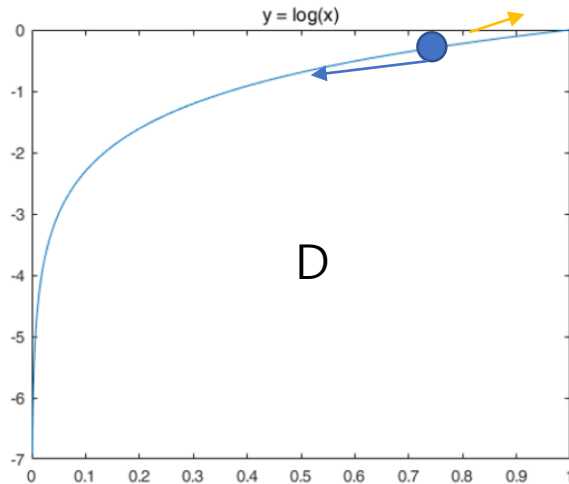


(b) Undamped or Sustained Oscillations

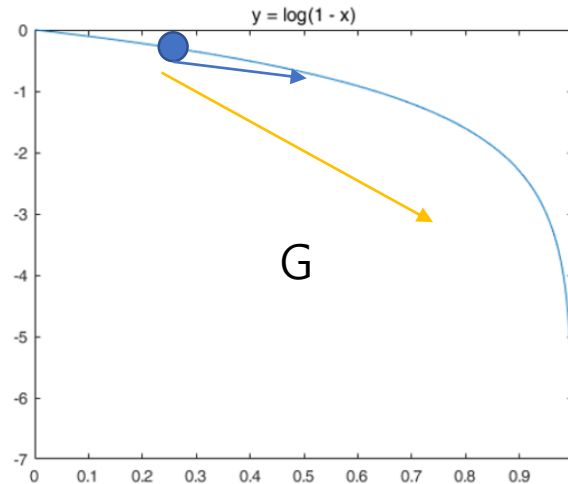
Damped and Undamped Oscillations

$f(\theta_G, \theta_D)$ is typically very far from convex in θ_G and concave in θ_D

$$f(\theta_G, \theta_D) = \min_G \max_D V(D, G) = \mathbb{E}_{\mathbf{x} \sim p_{\text{data}}(\mathbf{x})} [\log D(\mathbf{x})] + \mathbb{E}_{\mathbf{z} \sim p_{\mathbf{z}}(\mathbf{z})} [\log(1 - D(G(\mathbf{z})))].$$



Not concave in



Not convex



impossible

$$D_G^*(\mathbf{x}) = \frac{p_{\text{data}}(\mathbf{x})}{p_{\text{data}}(\mathbf{x}) + p_g(\mathbf{x})}$$

we will introduce a surrogate objective function $f_K(\theta_G, \theta_D)$

Surrogate objective function

$$f_K(\theta_G, \theta_D) = f(\theta_G, \theta_D^K(\theta_G, \theta_D))$$

Local optimum θ_D^*

$$\theta_D^0 = \theta_D$$

$$\theta_D^{k+1} = \theta_D^k + \eta^k \frac{df(\theta_G, \theta_D^k)}{d\theta_D^k}$$

$$\theta_D^* = \lim_{k \rightarrow \infty} \theta_D^k$$

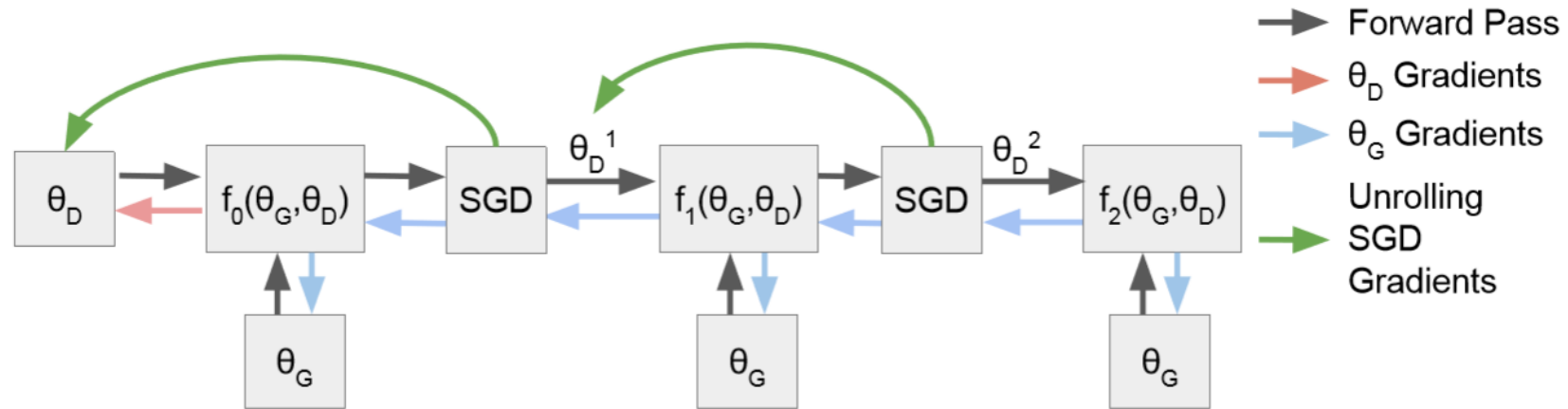
Update

$$\theta_G \leftarrow \theta_G - \eta \frac{df_K(\theta_G, \theta_D)}{d\theta_G}$$

$$\theta_D \leftarrow \theta_D + \eta \frac{df(\theta_G, \theta_D)}{d\theta_D}.$$



θ_D 업데이트에는 f_k 를 적용하지 않는다



What is different from standard gan?

- Standard gan: several update steps of the discriminator parameters should be run before each single update step for the generator

$$\theta_G \leftarrow \theta_G - \eta \frac{\partial f(\theta_G, \theta_D^K(\theta_G, \theta_D))}{\partial \theta_G}$$

- unrolled gan: several update steps of the discriminator parameters should be run before each single update step for the generator

$$\theta_G \leftarrow \theta_G - \eta \frac{df(\theta_G, \theta_D^K(\theta_G, \theta_D))}{d\theta_G}$$

$$\frac{df_K(\theta_G, \theta_D)}{d\theta_G} = \frac{\partial f(\theta_G, \theta_D^K(\theta_G, \theta_D))}{\partial \theta_G} + \frac{\partial f(\theta_G, \theta_D^K(\theta_G, \theta_D))}{\partial \theta_D^K(\theta_G, \theta_D)} \frac{d\theta_D^K(\theta_G, \theta_D)}{d\theta_G}.$$

the second term reflects that as the generator collapses towards a delta function

$$\frac{df_K(\theta_G, \theta_D)}{d\theta_G} = \frac{\partial f(\theta_G, \theta_D^K(\theta_G, \theta_D))}{\partial \theta_G} + \frac{\partial f(\theta_G, \theta_D^K(\theta_G, \theta_D))}{\partial \theta_D^K(\theta_G, \theta_D)} \frac{d\theta_D^K(\theta_G, \theta_D)}{d\theta_G}.$$

Delta function: An optimal generator for any fixed discriminator

When $K = 0$ and when $K \rightarrow \infty$
: standard Gan loss = unrolled gan loss

$K = 0$

$$f_K(\theta_G, \theta_D) = f(\theta_G, \theta_D^K(\theta_G, \theta_D))$$

$$\theta_D^0 = \theta_D$$

$$f_0(\theta_G, \theta_D) = f(\theta_G, \theta_D^0) = f(\theta_G, \theta_D)$$

$K = \infty$

$$f_K(\theta_G, \theta_D) = f(\theta_G, \theta_D^K(\theta_G, \theta_D))$$

$$\theta_D^* = \lim_{k \rightarrow \infty} \theta_D^k$$

$$f_\infty(\theta_G, \theta_D) = f(\theta_G, \theta_D^\infty) = f(\theta_G, \theta_D^*)$$

$K=1,2,3, \dots$

$f_k(\theta_G, \theta_D)$ captures additional information about the response of the discriminator to changes in the generator

$$\frac{df_K(\theta_G, \theta_D)}{d\theta_G} = \frac{\partial f(\theta_G, \theta_D^K(\theta_G, \theta_D))}{\partial \theta_G} + \frac{\partial f(\theta_G, \theta_D^K(\theta_G, \theta_D))}{\partial \theta_D^K(\theta_G, \theta_D)} \frac{d\theta_D^K(\theta_G, \theta_D)}{d\theta_G}.$$