# Generative Model GAN + DCGAN

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DAVIAN Lab Study
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3. DCGAN

4. TensorFlow Implementation

#### **Table of Contents**

1. Generative Model

2. GAN

3. **DCGAN** Code에 대한 분석을 하고 싶다면 여기로 (p.88)

4. TensorFlow Implementation

"What I cannot create, I do not understand."

—Richard Feynman

# mage Modeling

Language Modeling이 있듯이 Image Modeling도 존재한다

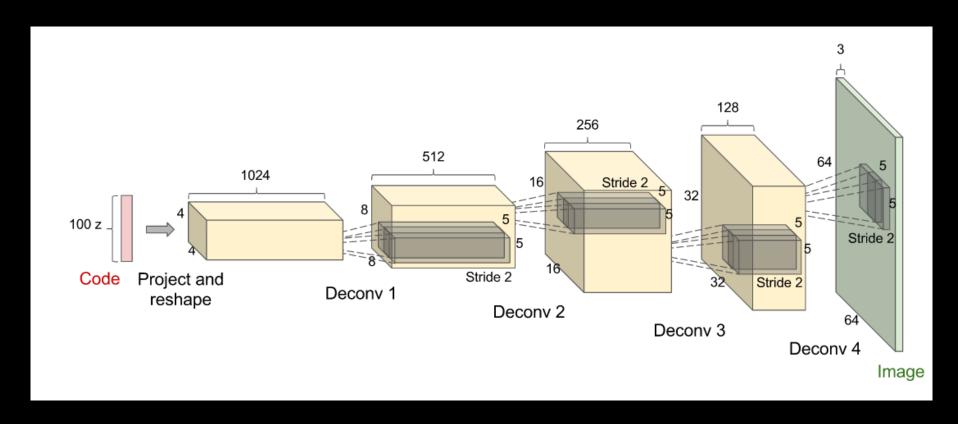
적은 수의 parameter로 image data의 distribution 함수를 만드는게 목표



120만 개의 imagenet dataset 1.2M x 256 x 256 x 3 (약 200GB의 pixel data)

#### **Image Modeling**

Code가 주어지면 Imagenet 데이터셋을 생성하는 모델



100MB of weights < 200GB of pixels

Generative Adversarial
Networks

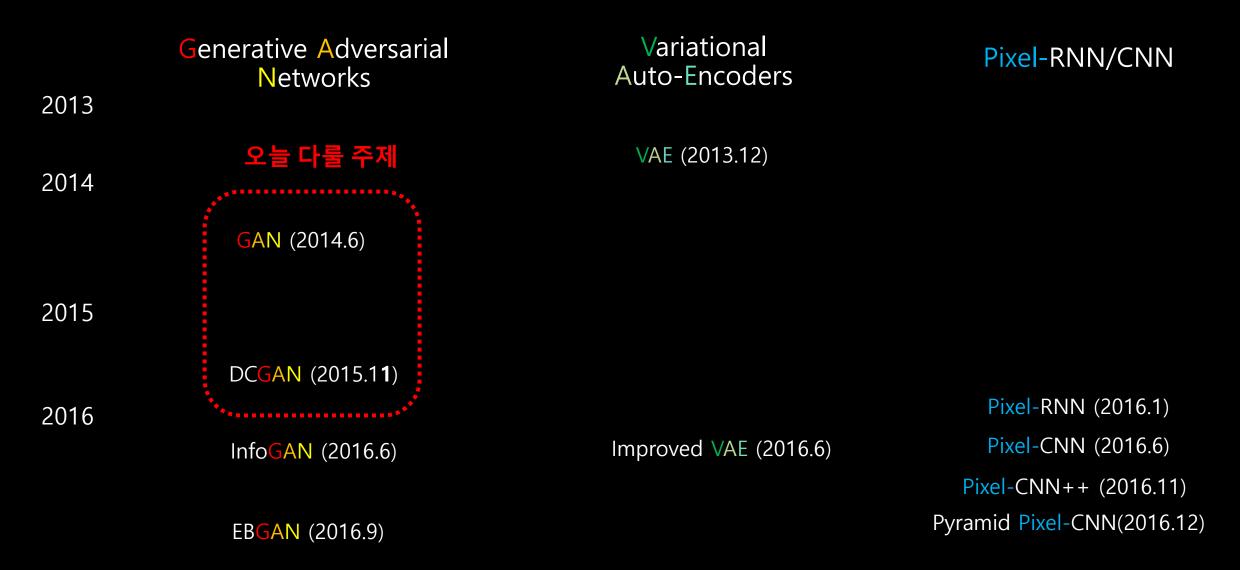
Variational Auto-Encoders

Pixel-RNN/CNN

생성자와 식별자 두 모델 간의 적대적 학습 (Adversarial Learning) 문제를 PGM형태로 치환 후 data의 log likelihood lower bound를 maximize하는 쪽으로 학습

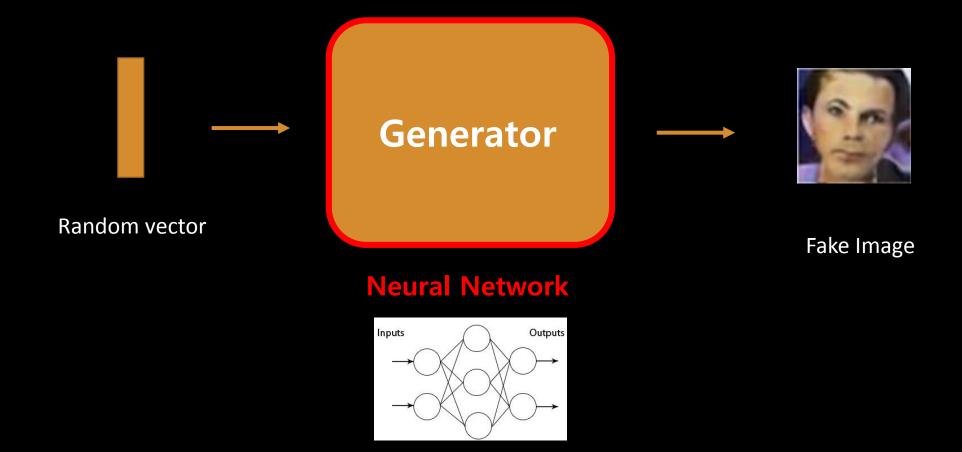
모든 pixel들의 conditional distribution을 modeling (left-to-right, top-to-bottom)

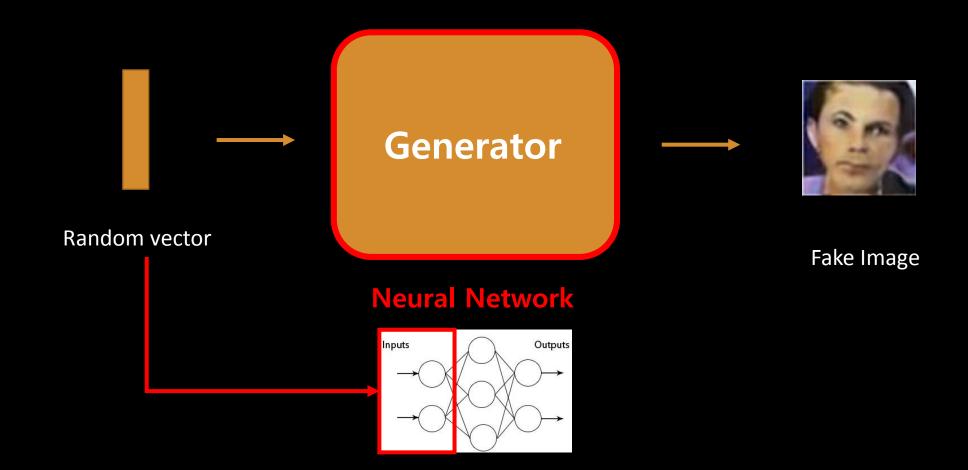
	Generative Adversarial Networks	Variational Auto-Encoders	Pixel-RNN/CNN
2013			
		VAE (2013.12)	
2014			
	GAN (2014.6)		
2015			
	DCGAN (2015.1 <b>1</b> )		
2016			Pixel-RNN (2016.1)
	InfoGAN (2016.6)	Improved VAE (2016.6)	Pixel-CNN (2016.6)
			Pixel-CNN++ (2016.11)
	EBGAN (2016.9)		Pyramid Pixel-CNN(2016.12)

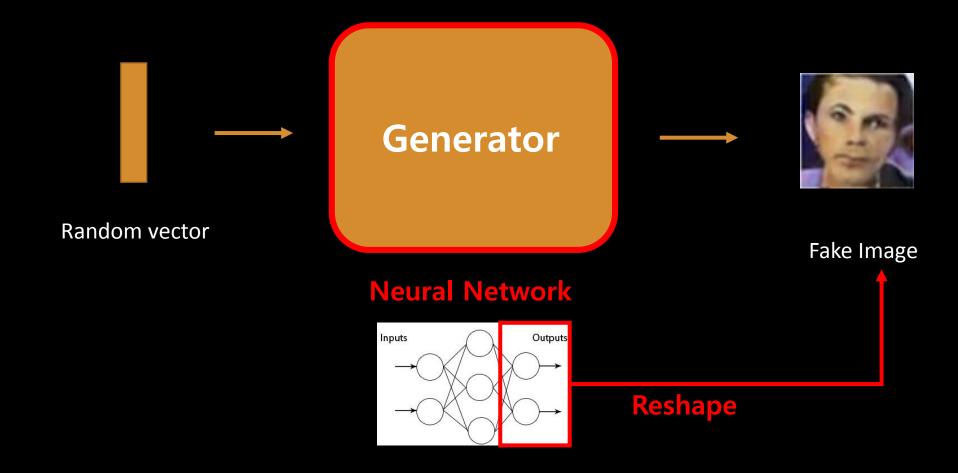


# 2. GAN



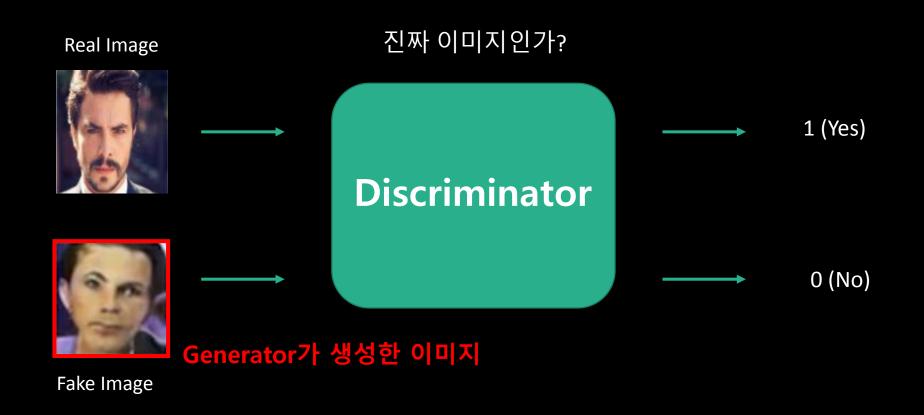


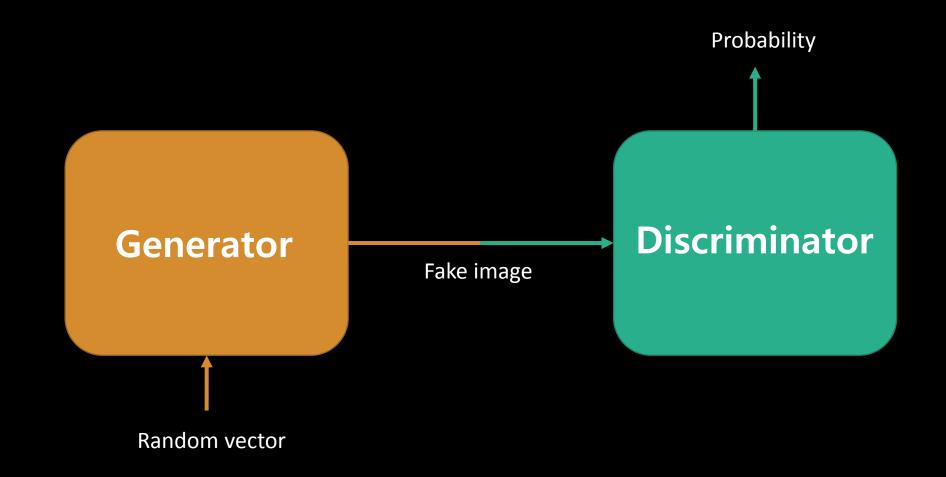


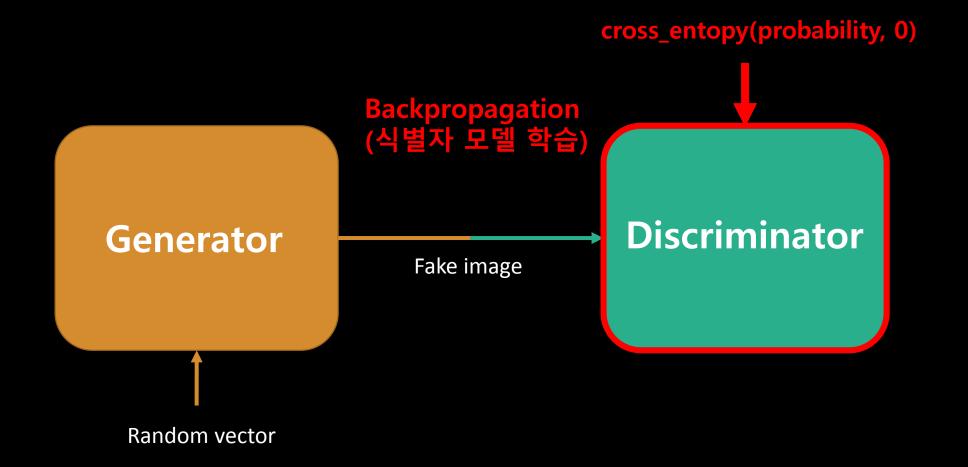


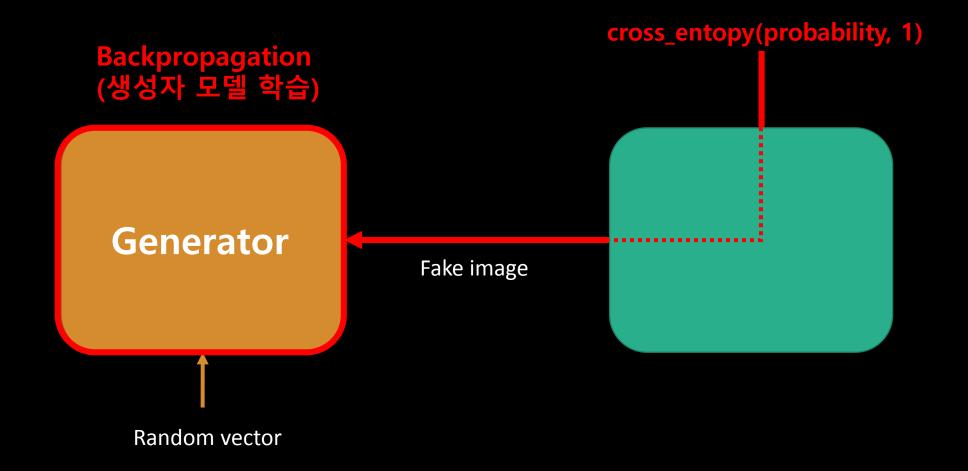


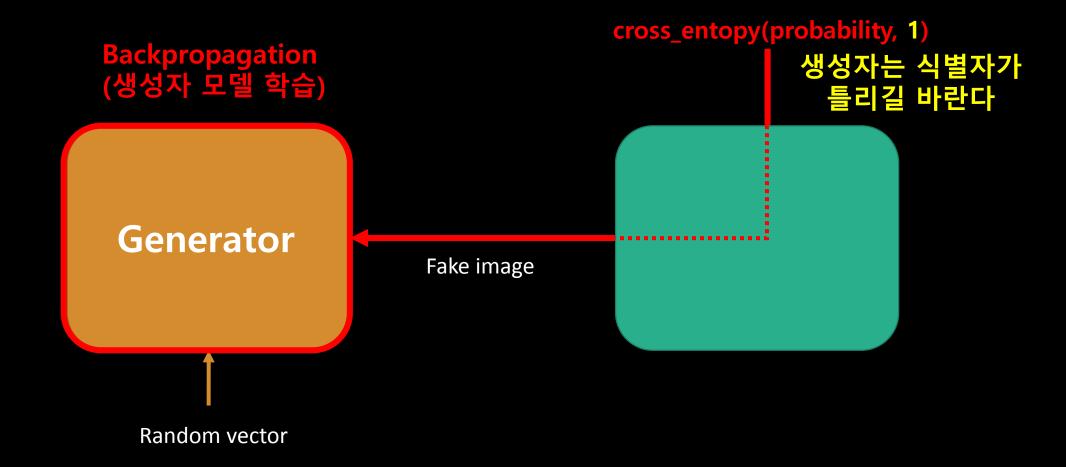


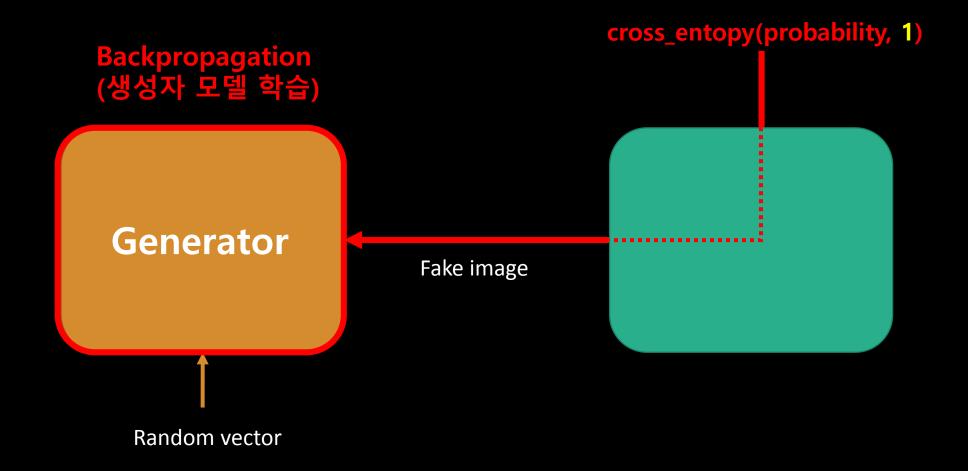


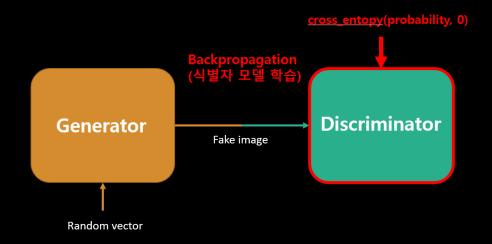


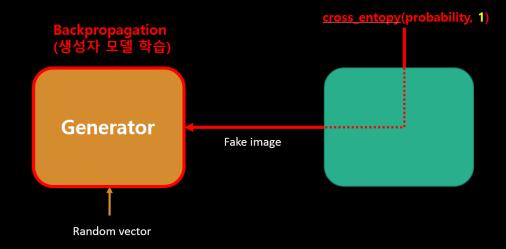


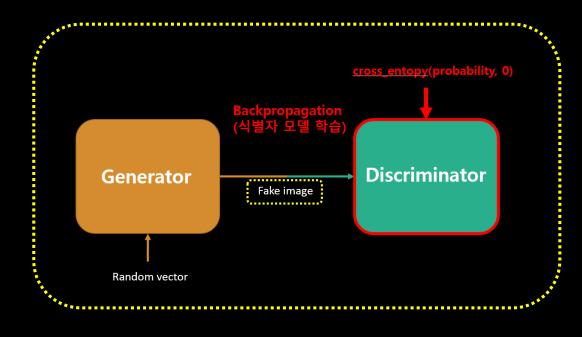




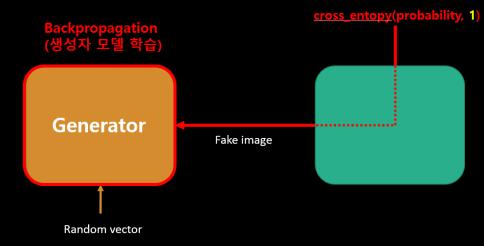


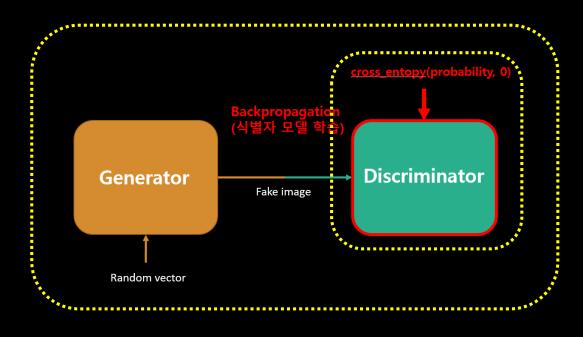




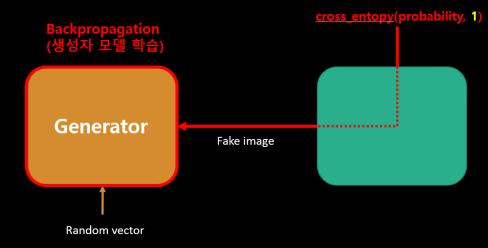


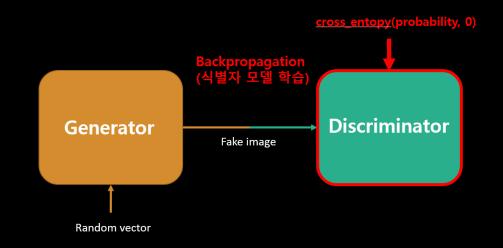
생성자는 가짜 이미지를 생성하고

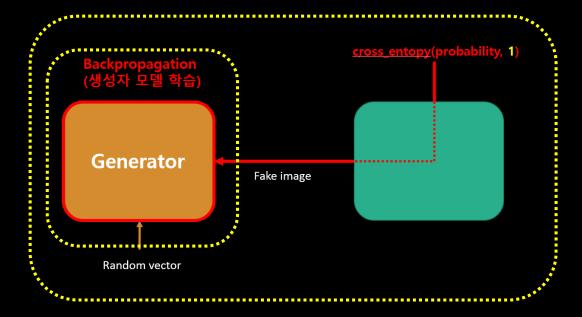




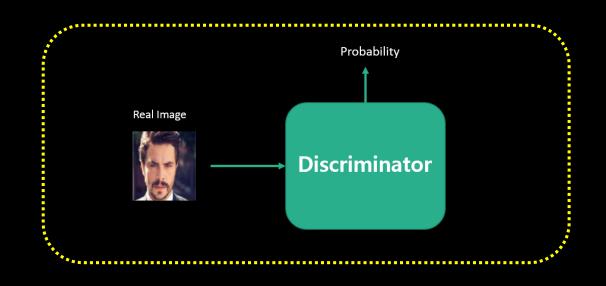
식별자는 가짜이미지를 '가짜'라고 판별하도록 학습



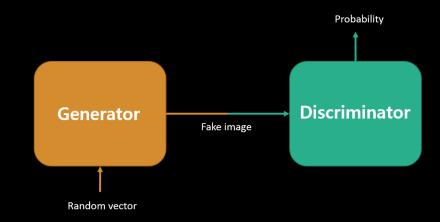




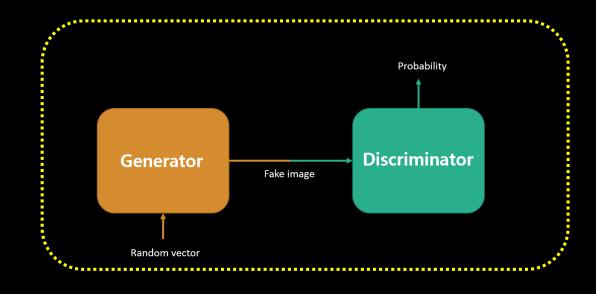
생성자는 식별자가 '가짜'를 '진짜'로 판별하도록 학습



진짜 이미지를 가지고 학습할 때 구조 (식별자만 학습)



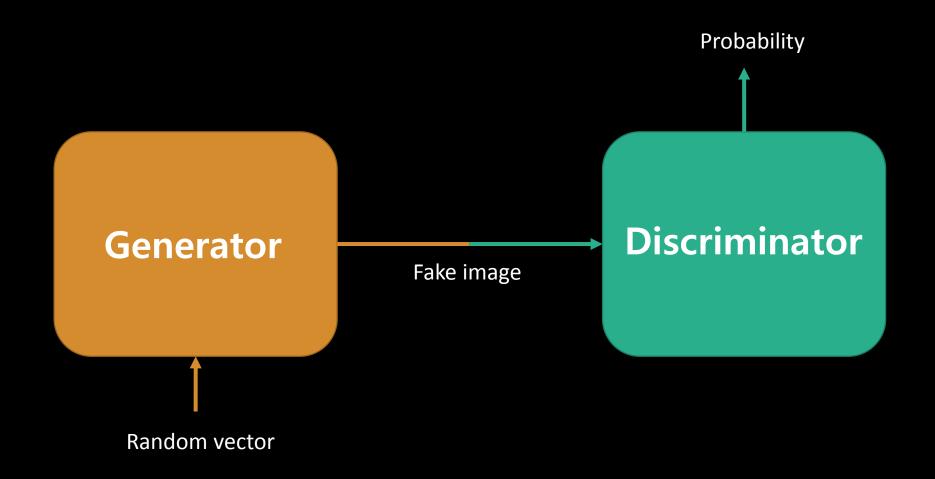




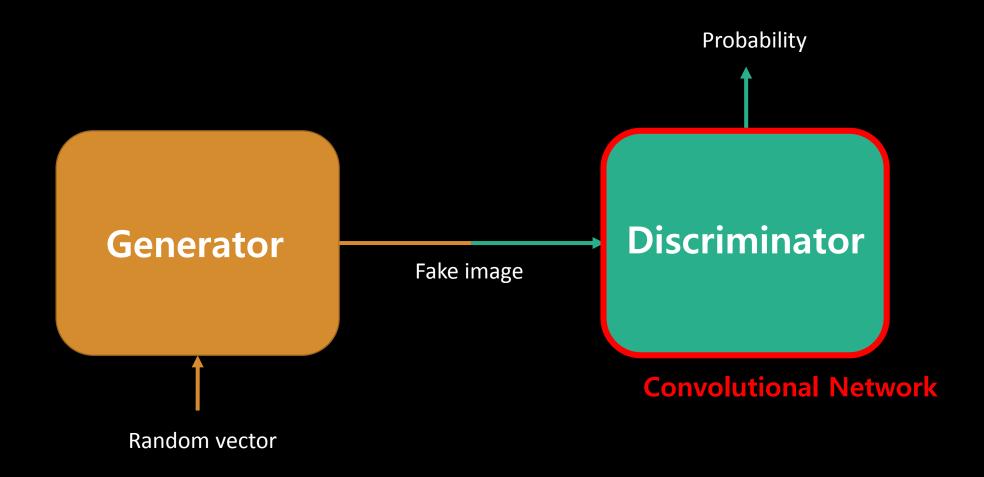
가짜 이미지를 가지고 학습할 때 구조 (식별자와 생성자 모두 학습)

# 3. DCGAN

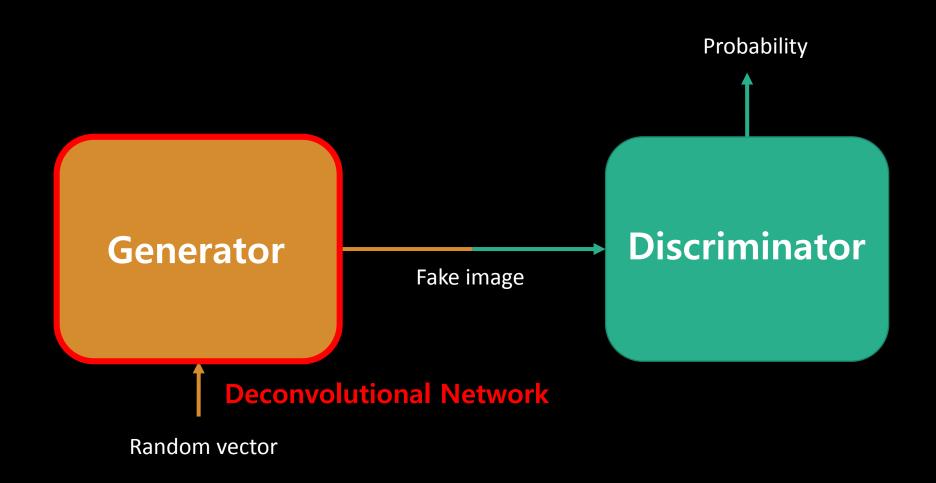
## Deep Convolutional GAN (DCGAN)



## Deep Convolutional GAN (DCGAN)

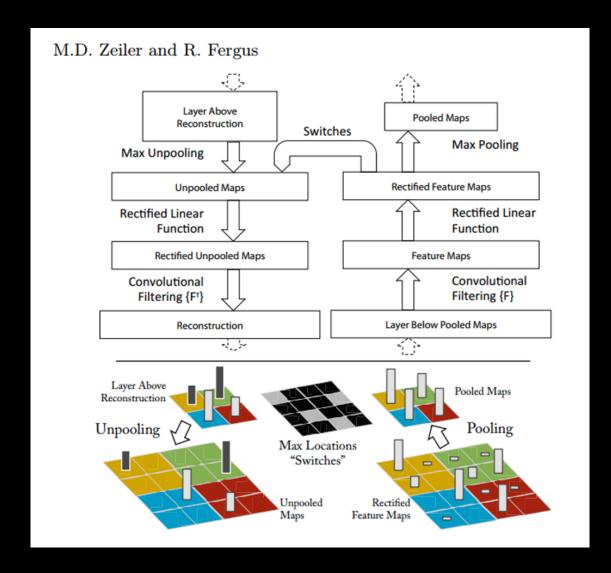


## Deep Convolutional GAN (DCGAN)

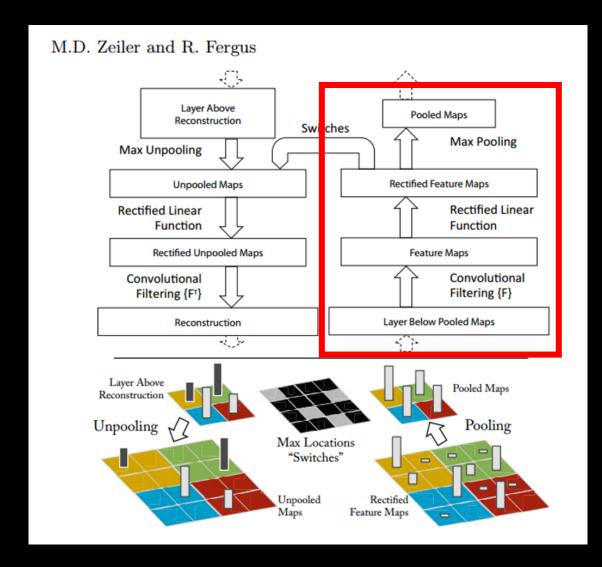


# Deconvolution?

#### Deconvolutional Neural Network



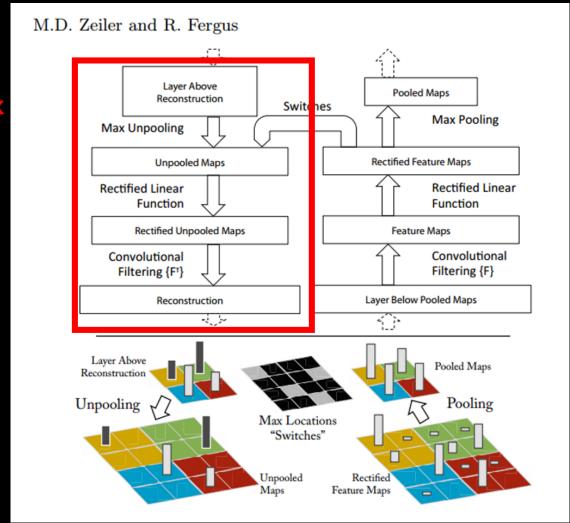
#### **Deconvolutional Neural Network**



**Convolutional Network** 

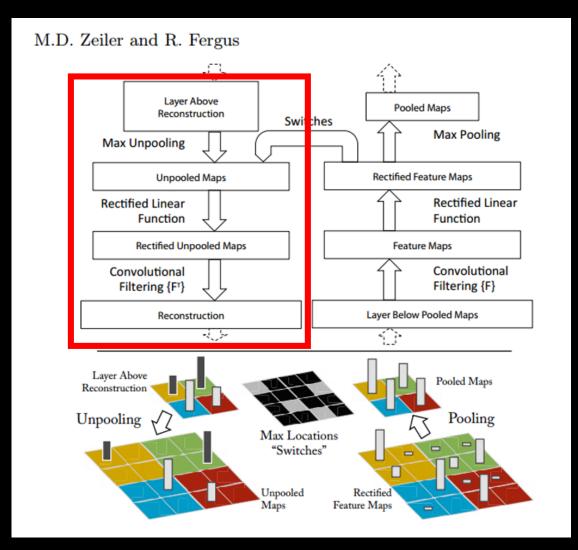
#### **Deconvolutional Neural Network**

**Deconvolutional Network** 



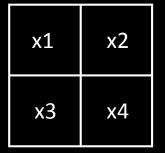
#### Deconvolutional Neural Network

Deconvolutional Network = CNN Backpropagation



visualizing and understanding convolutional networks (2013)

convolution forward

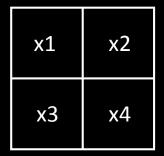




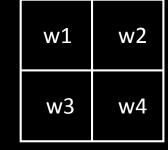
w1	w2
w3	w4



convolution forward

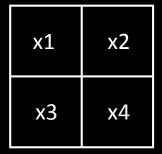






 $y1 = w1 \cdot x1 + w2 \cdot x2 + w3 \cdot x3 + w4 \cdot x4$ 

## convolution forward





w1	w2
w3	w4

=

$$y1 = w1 \cdot x1 + w2 \cdot x2 + w3 \cdot x3 + w4 \cdot x4$$

convolution backward

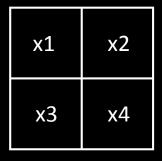
dx1	dx2
dx3	dx4



w1	w2
w3	w4

dy1

## convolution forward





w1	w2
w3	w4

$$y1 = w1 \cdot x1 + w2 \cdot x2 + w3 \cdot x3 + w4 \cdot x4$$

convolution backward

dx1	dx2
dx3	dx4

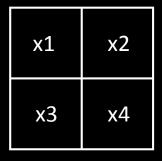




 $dy1 = \frac{\partial L}{\partial y_1}$ 

(L은 loss값)

## convolution forward





w1	w2
w3	w4

$$y1 = w1 \cdot x1 + w2 \cdot x2 + w3 \cdot x3 + w4 \cdot x4$$

convolution backward

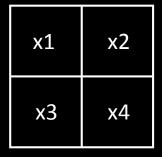


w1	w2
w3	w4

$$dy1 = \frac{\partial L}{\partial y_1}$$

dx1 = ?

convolution forward





w1	w2
w3	w4

 $y1 = w1 \cdot x1 + w2 \cdot x2 + w3 \cdot x3 + w4 \cdot x4$ 

convolution backward

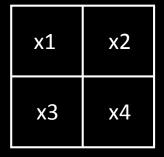
dx1	dx2
dx3	dx4



w1	w2
w3	w4

 $dy1 = \frac{\partial L}{\partial y_1}$ 

convolution forward





**y**1

$$y1 = w1 \cdot x1 + w2 \cdot x2 + w3 \cdot x3 + w4 \cdot x4$$

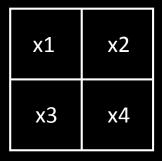
convolution backward



w1	w2
w3	w4

 $dy1 = \frac{\partial L}{\partial y1}$ 

### convolution forward





w1	w2
w3	w4

y1

$$y1 = w1 \cdot x1 + w2 \cdot x2 + w3 \cdot x3 + w4 \cdot x4$$

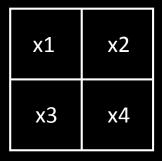
convolution backward



 $dx1 = \frac{\partial L}{\partial x1} = \frac{\partial L}{\partial y1} \frac{\partial y1}{\partial x1} = dy1 \cdot w1$ 

w1	w2
w3	w4

### convolution forward





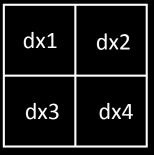
w1	w2
w3	w4

=

**y1** 

$$y1 = w1 \cdot x1 + w2 \cdot x2 + w3 \cdot x3 + w4 \cdot x4$$

convolution backward





w1	w2
w3	w4

$$\partial y$$

$$dx1 = \frac{\partial L}{\partial x1} = \frac{\partial L}{\partial y1} \frac{\partial y1}{\partial x1} = dy1 \cdot w1 \longrightarrow dxi = dy1 \cdot wi \quad (1 \le i \le 4)$$

#### 숫자로 예를 들어보자

convolution backward

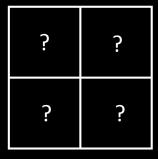




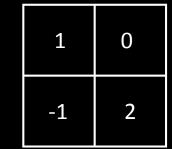
1	0
-1	2

$$dy1 = \frac{\partial L}{\partial y1}$$

convolution backward





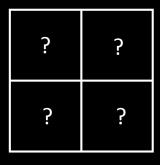


위에 있는 layer로 부터 받은 미분 값

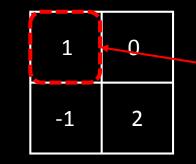


 $dy1 = \frac{\partial L}{\partial y1}$ 

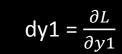
convolution backward



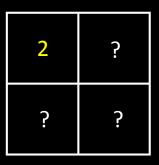




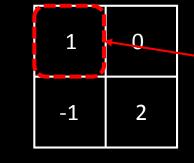
위에 있는 layer로 부터 받은 미분 깂



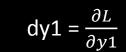
convolution backward





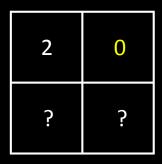


위에 있는 layer로 부터 받은 미분 값

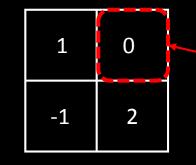


$$dxi = dy1 \cdot wi \ (1 \le i \le 4)$$
  $i = 1$ 

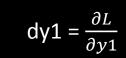
convolution backward





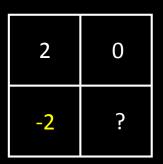


위에 있는 layer로 부터 받은 미분 값

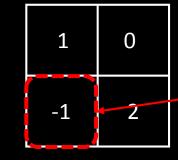


$$dxi = dy1 \cdot wi \ (1 \le i \le 4)$$
  $i = 2$ 

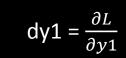
convolution backward







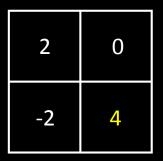
위에 있는 layer로 부터 받은 미분 깂



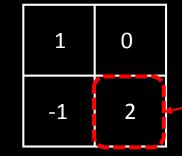
$$dxi = dy1 \cdot wi \ (1 \le i \le 4)$$

$$i = 3$$

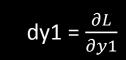
convolution backward





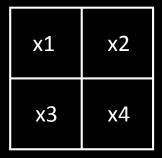


위에 있는 layer로 부터 받은 미분 깂



$$dxi = dy1 \cdot wi \ (1 \le i \le 4)$$

## deconvolution forward





w1	w2
w3	w4

y1

$$xi = y1 \cdot wi \ (1 \le i \le 4)$$

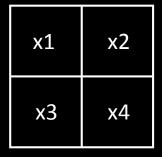
convolution backward

dx1	dx2
dx3	dx4

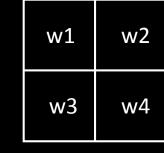


dy1

## deconvolution forward







**y1** 

 $xi = y1 \cdot wi \ (1 \le i \le 4)$ 

convolution backward

dx1	dx2
dx3	dx4

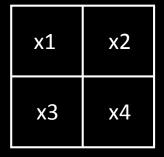


w1	w2
w3	w4

위에 있는 layer도 부터 받은 미문 û

dy1

deconvolution forward





w1	w2
w3	w4

아래에 있는 layer로 부터 받은 activation 값



 $xi = y1 \cdot wi \ (1 \le i \le 4)$ 

convolution backward

dx1	dx2
dx3	dx4

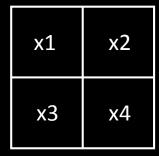


w1	w2
w3	w4

위에 있는 layer로 부터 받은 미분 깂



deconvolution forward



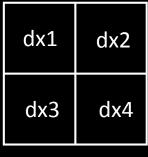


w1	w2
w3	w4

아래에 있는 layer로 부터 받은 activation 값



convolution backward





w1	w2
w3	w4



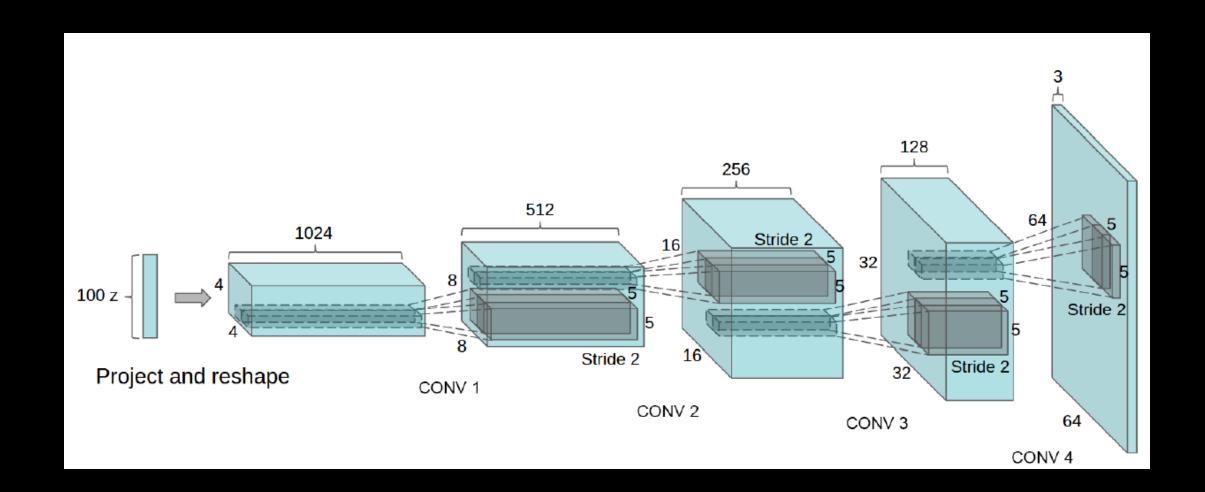
# 결론은

**Convolution Backward = Deconvolution Forward** 

**Convolution Forward = Deconvolution Backward** 

**DAVIAN Lab** 

# 다시 DCGAN으로 돌아와서



**Discriminator** = Convolutional Network

**Generator**= Deconvolutional Network

#### 이전에도 CNN과 DCNN을 사용한 연구는 많았지만 DCGAN에서 다른 점이 있다

1. Pooling Layer를 사용하지 않음 -> All Strided Convolution

Pooling Layer를 사용하게 되면 Blocky한 이미지들이 생성되는데 이를 방지

Striving for simplicity: The all convolutional net (2014) 에서 아이디어를 얻음

#### 이전에도 CNN과 DCNN을 사용한 연구는 많았지만 DCGAN에서 다른 점이 있다

- 1. Pooling Layer를 사용하지 않음
  - 2. Batch Normalization

CNN과 DCNN에 Batch Normalization Layer를 추가

#### 이전에도 CNN과 DCNN을 사용한 연구는 많았지만 DCGAN에서 다른 점이 있다

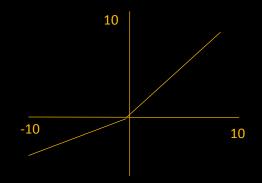
- 1. Pooling Layer를 사용하지 않음
  - 2. Batch Normalization 사용
- 3. Fully Connected Layer 최소화 -> All Convolution Layer

Generator의 첫 번째 layer와 Discriminator의 마지막 layer를 제외하고는 모두 Convolution Layer를 사용

Going deeper into neural networks (2015)에서 아이디어를 얻음

#### 이전에도 CNN과 DCNN을 사용한 연구는 많았지만 DCGAN에서 다른 점이 있다

- 1. Pooling Layer를 사용하지 않음
  - 2. Batch Normalization 사용
- 3. Fully Connected Layer 최소화

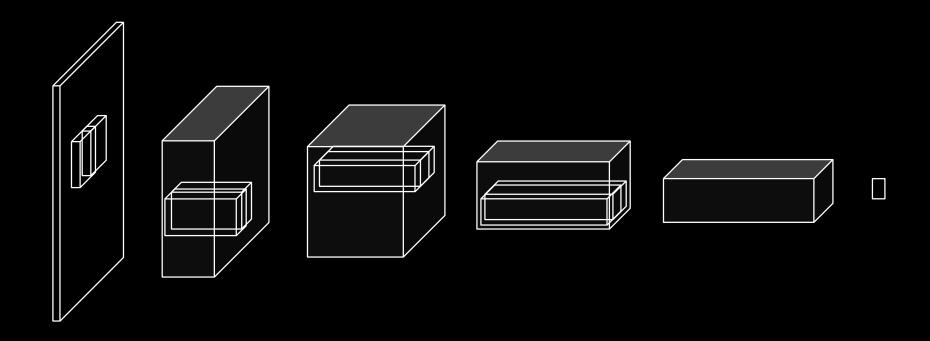


4. ReLU와 Leaky ReLU 사용 Generator는 ReLU를 사용, Discriminator는 Leaky ReLu를 사용 실험적으로 더 높은 퀄리티의 이미지를 생성

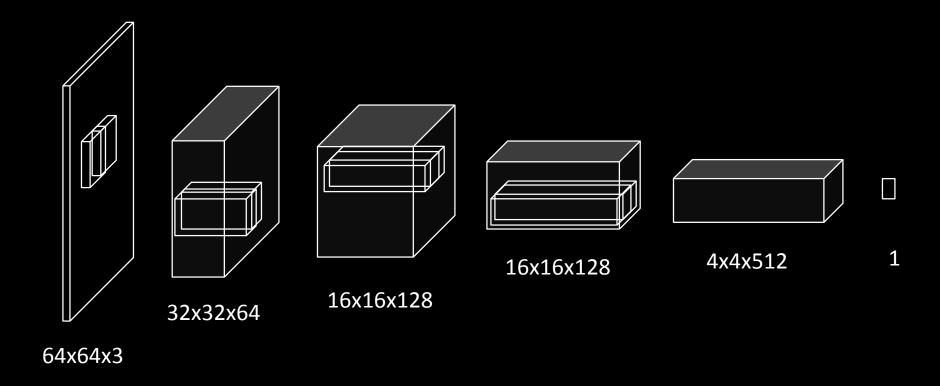
#### 이전에도 CNN과 DCNN을 사용한 연구는 많았지만 DCGAN에서 다른 점이 있다

- 1. Pooling Layer를 사용하지 않음
  - 2. Batch Normalization 사용
- 3. Fully Connected Layer 최소화
  - 4. ReLU와 Leaky ReLU 사용

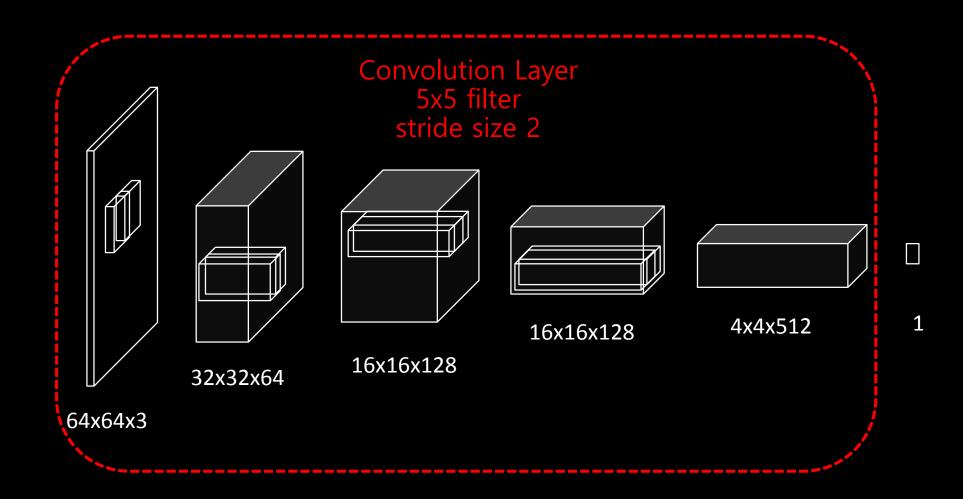
결과적으로 이전 연구보다 퀄리티가 더 높은 이미지를 생성

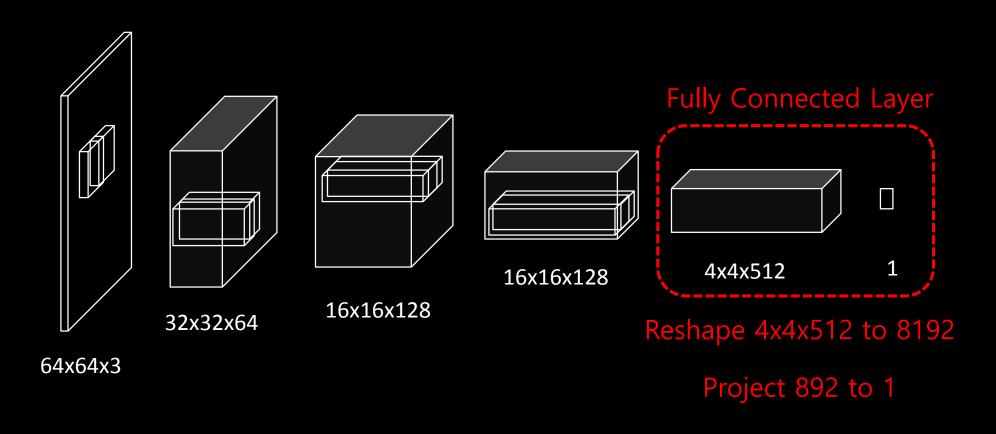


**DAVIAN Lab** 

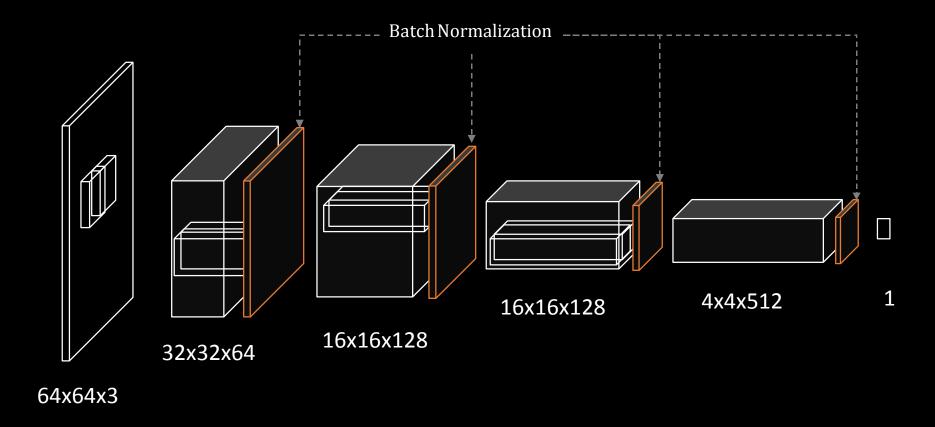


**DAVIAN Lab** 

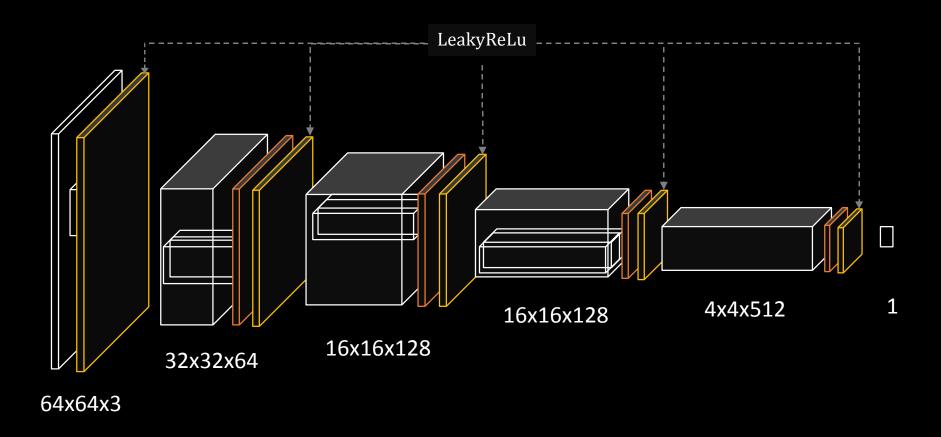


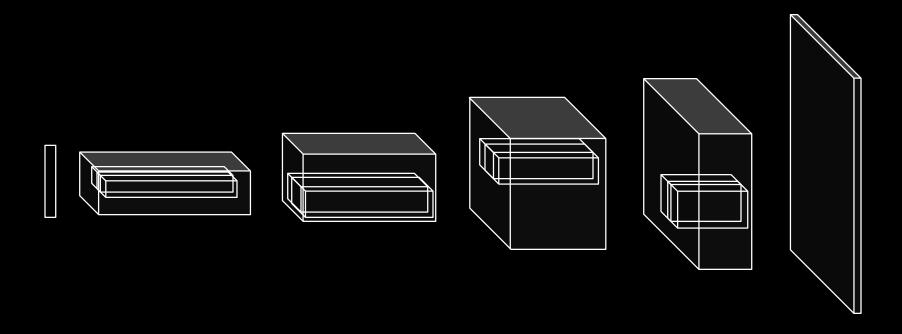


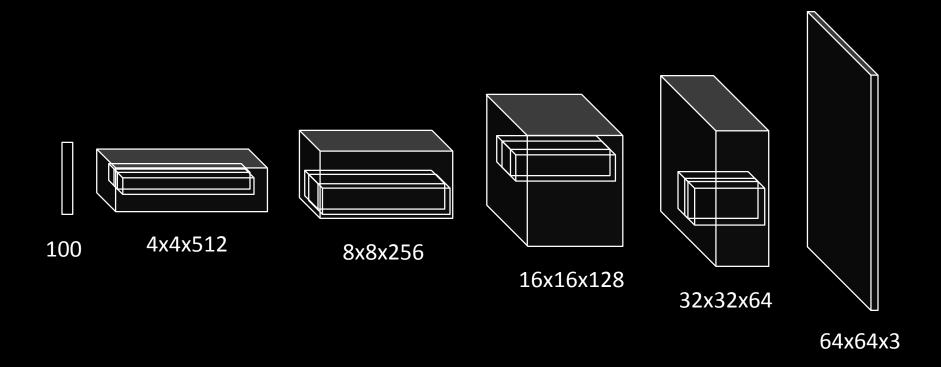
**DAVIAN Lab** 

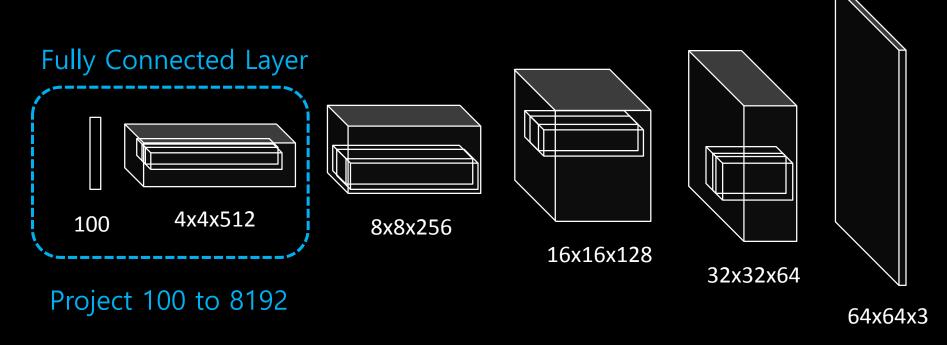


# Discriminator(식별자)

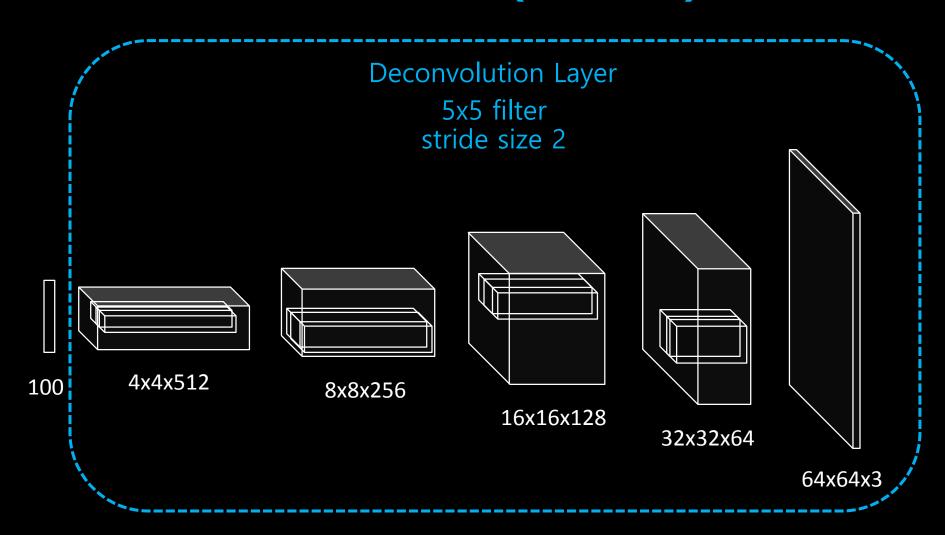


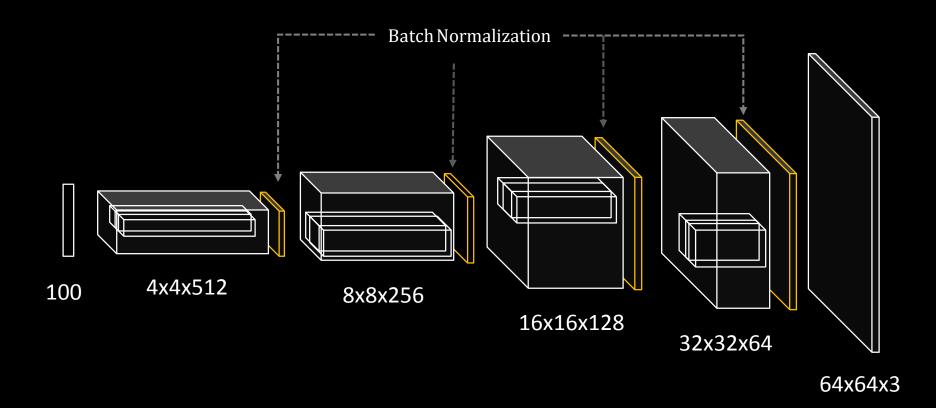


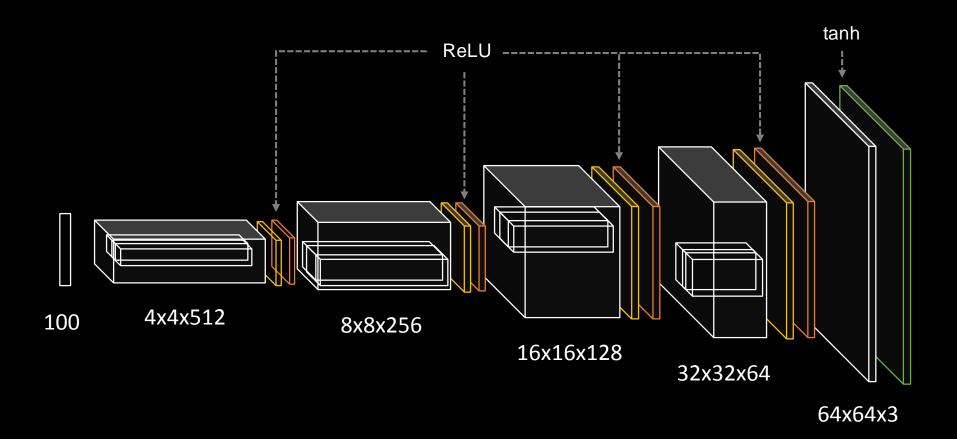


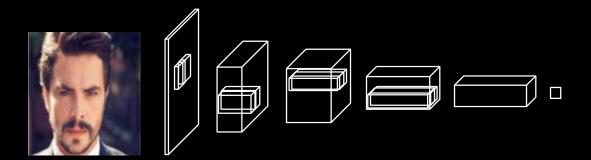


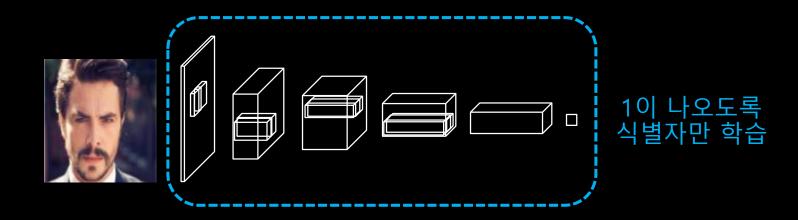
Reshape 8192 to 4x4x512

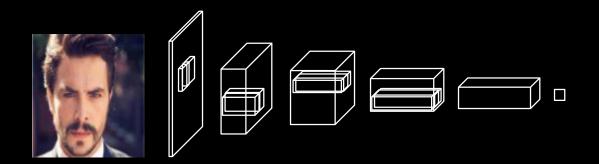




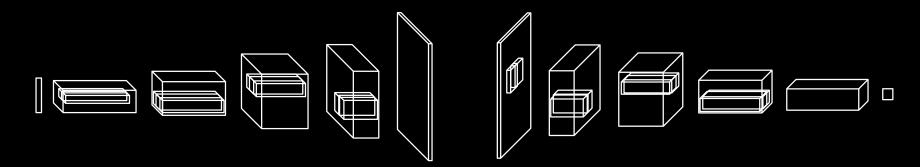


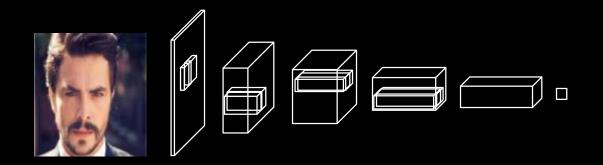




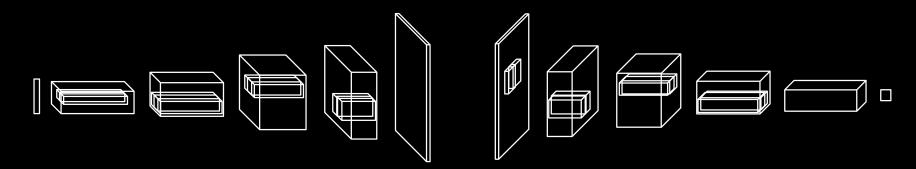


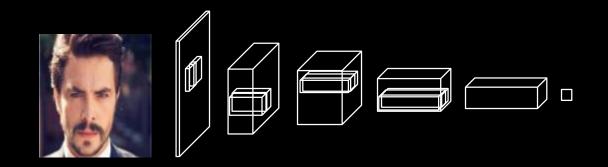
#### 가짜 이미지



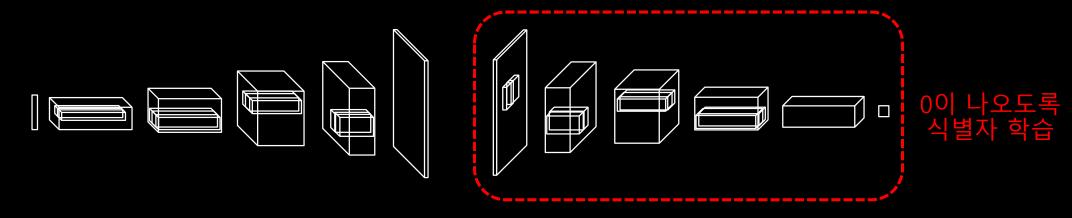


#### 가짜 이미지

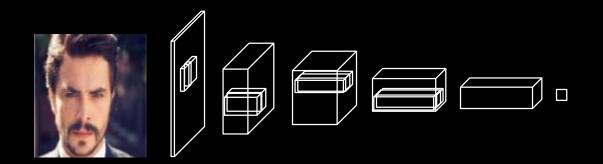




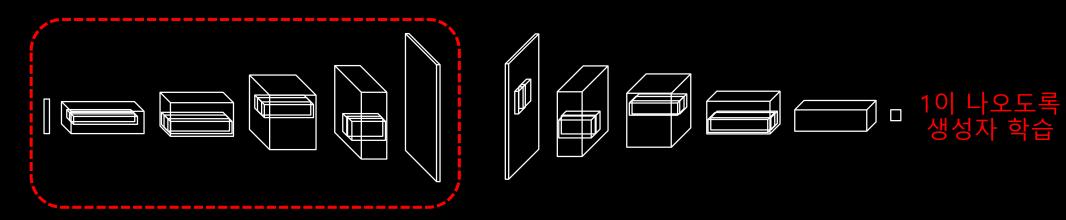
#### 가짜 이미지

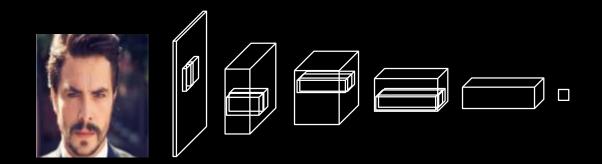


**DAVIAN Lab** 

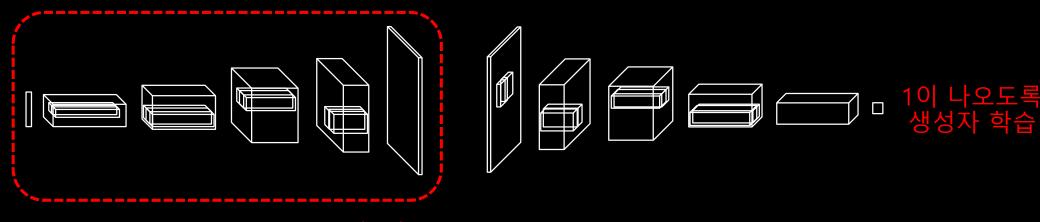


#### 가짜 이미지

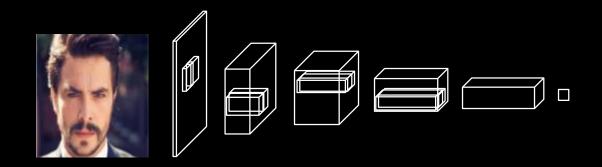


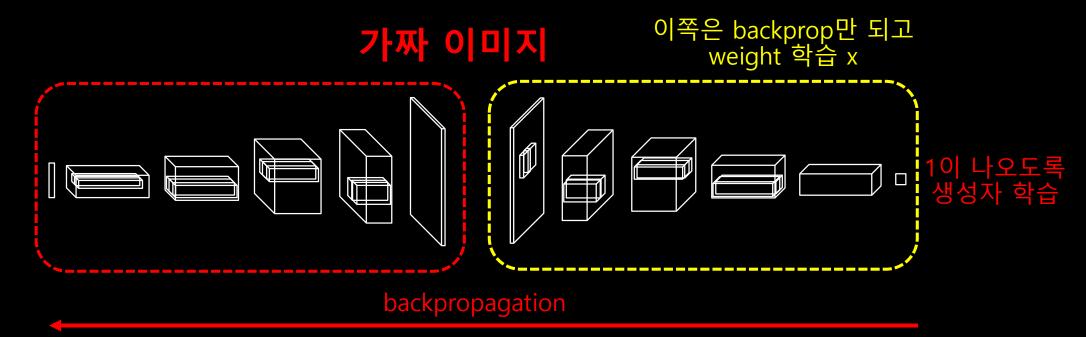


#### 가짜 이미지

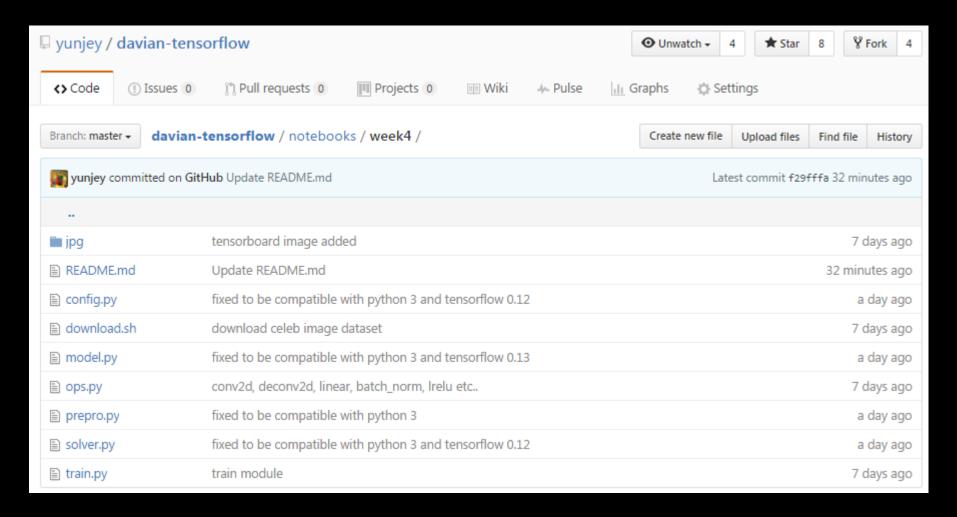


backpropagation

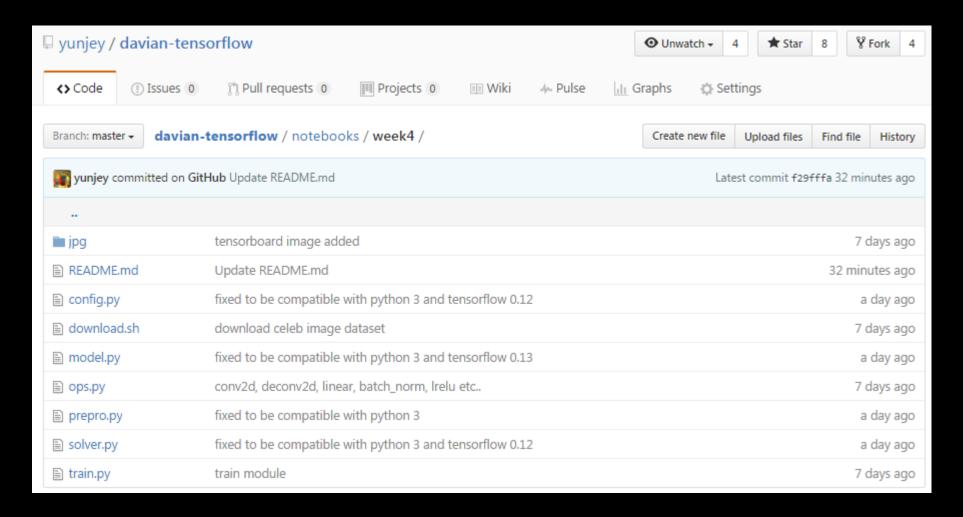




**DAVIAN Lab** 



https://github.com/yunjey/davian-tensorflow/tree/master/notebooks/week4



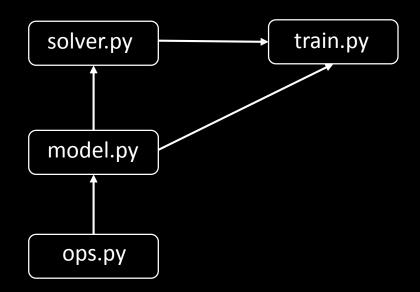
#### 먼저 코드 구조부터 파악해보자

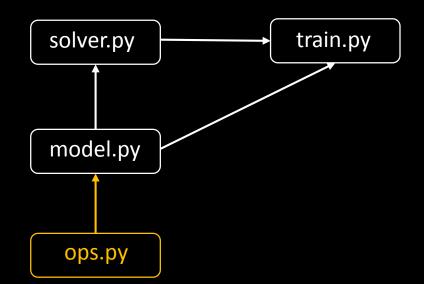
DAVIAN Lab

#### 아래 3개가 핵심 코드!

a config.py	fixed to be compatible with python 3 and tensorflow 0.12	a day ago
download.sh	download celeb image dataset	7 days ago
model.py	fixed to be compatible with python 3 and tensorflow 0.13	a day ago
☐ ops.py	conv2d, deconv2d, linear, batch_norm, Irelu etc	7 days ago
prepro.py	fixed to be compatible with python 3	a day ago
solver.py	fixed to be compatible with python 3 and tensorflow 0.12	a day ago
train.py	train module	7 days ago

DAVIAN Lab

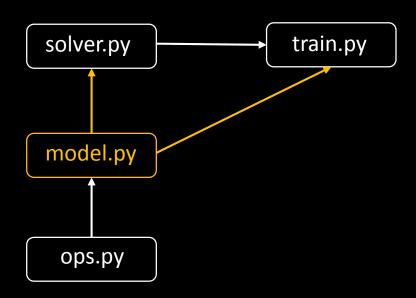




convolution, deconvolution과 같은 연산자들을 정의

DCGAN 모델을 정의 discriminator와 generator 정의

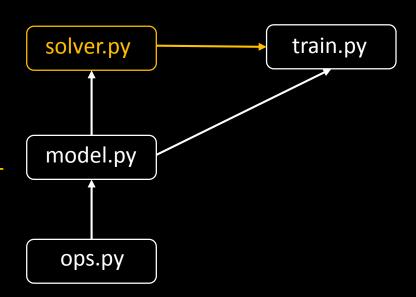
build\_model 함수호출 시 TensorFlow Graph를 생성



학습 데이터를 불러온 뒤 DCGAN 모델을 학습

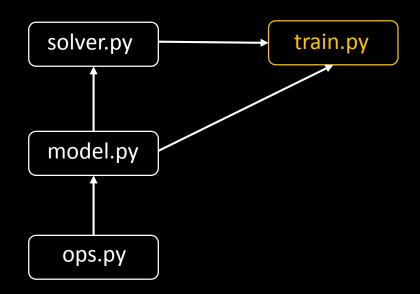
\_\_init\_\_ 함수에서 build\_model 호출

train 함수 호출 시 Session이 실행되고 학습시작

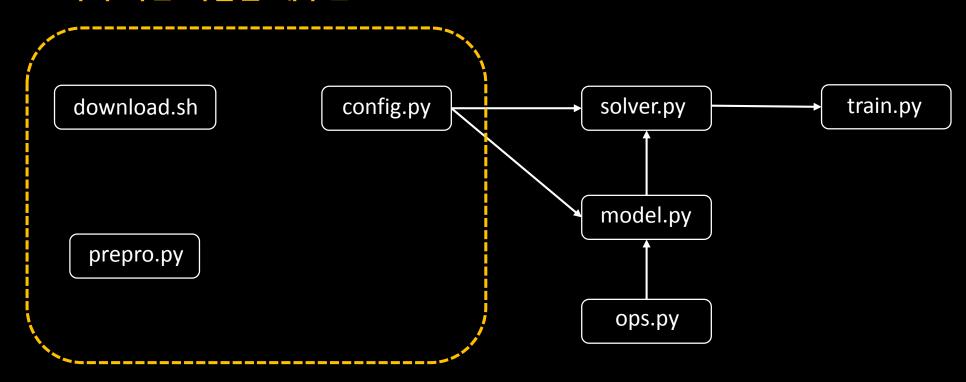


DCGAN model을 생성

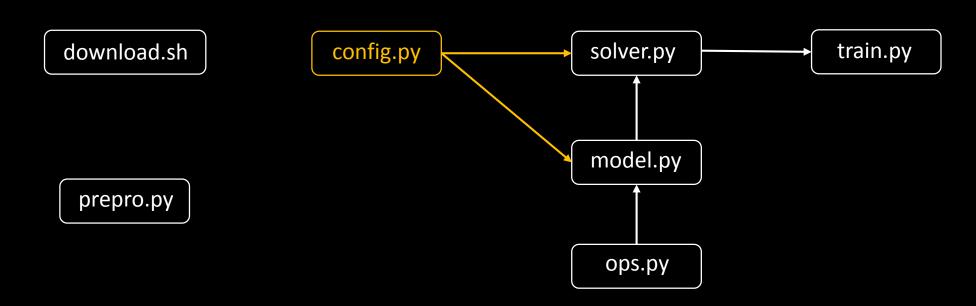
Solver를 통해 DCGAN 모델을 학습



#### 부수적인 역할을 해주는 module



#### TensorFlow 0.11과 0.12 버전 모두 호환이 되게 설정



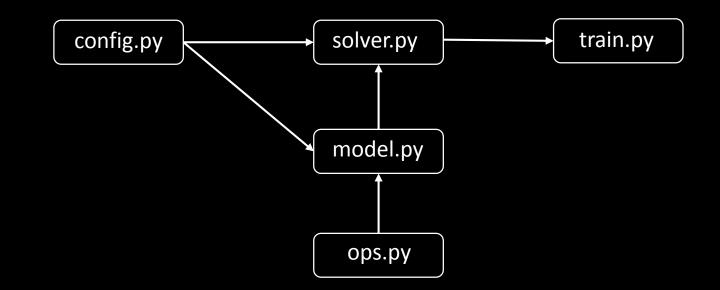
TensorFlow 0.11 -> 0.12 바뀐점

- 1. Variable -> Global Variable로 명칭이 바뀜
- 2. Tensorboard를 위한 함수들을 부르는 방식이 바뀜

#### CelebA 이미지 데이터셋 다운로드

download.sh

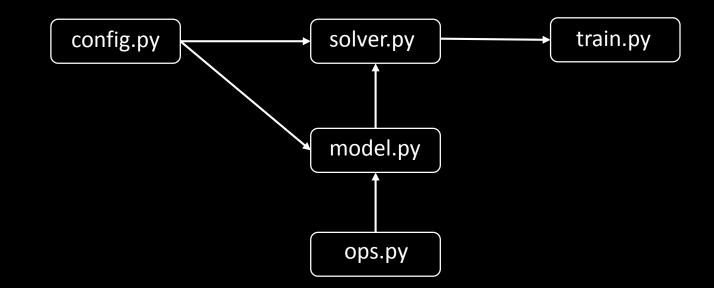
prepro.py



#### CelebA 이미지를 64x64 형태로 center crop한 후 resize

download.sh

prepro.py



- 1. ops.py에서 batch\_norm만 class로 구현한 이유는?
- 2. model.py에서 sampled images(57번째 줄)를 생성할 때 batch\_norm 함수가 moving average와 variance를 사용하는가?

(사용하지 않는 다면 사용하게끔 코드를 수정하시오)

# Thank You