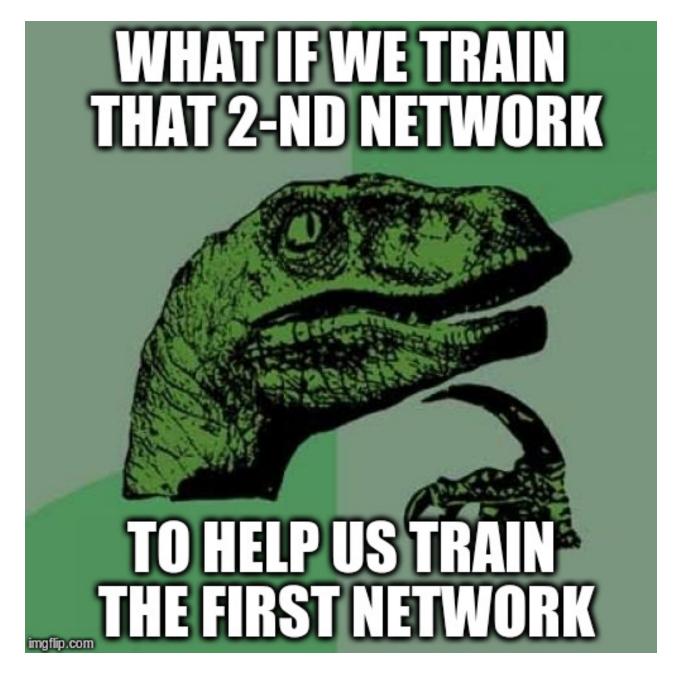
Lets train a model to tell us whether a generated image is good enough or not.



This is the high level overview.

GENERATOR VS

DISCRIMINATOR.





content

feedback

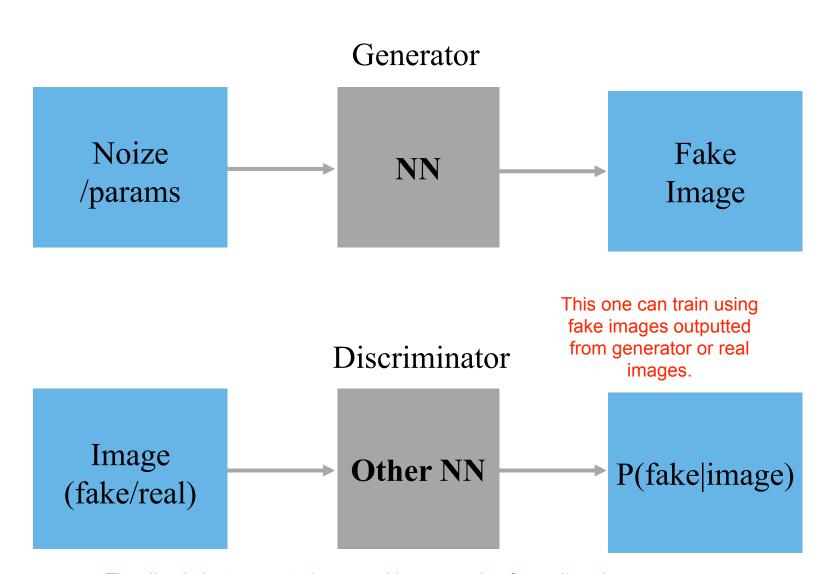
Discriminator



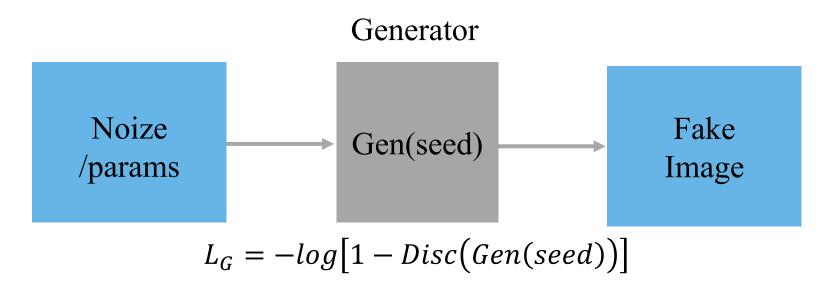
Generate image (should be plausible)

Tell if image is plausible $(image) \rightarrow P(fake)$

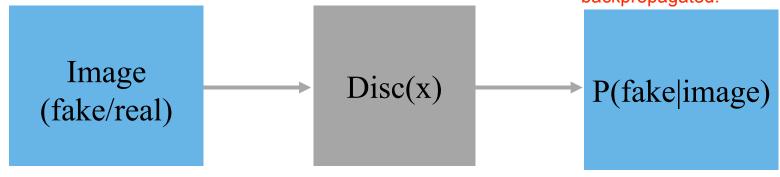
called discriminator because it discriminates between real images and the generated images.



The discriminator can train on positive examples from all real images, and negative examples using all generated fake images.



Discriminator operators which makes it able to be backpropagated.



$$L_D = -log[1 - Disc(realdata)] - logDisc(Gen(seed))$$

Algorithm

- sample noise z and images x
- for k in 1...K
 - Train discriminator(x), discriminator(generator(z))
- For m in 1...M

^these are the positive samples.

^these are the negative samples.

• Train generator(z)

Generative models are unstable. You have two models that 'hate each other'. And if one of them wins, you have to start the process all over again.

If discriminator wins (can train faster than generator), then the gradients vanish - the sigmoids that are used to compute P(real | image) are really close to 1 or 0.

Thus, they have very small gradient.

If generator wins (constantly train faster than discriminator), then it can start learning the wrong things.

The generator can learn non-sensical stuff.

training steps:

(0). initialize generator and discriminator weights randomly.

- (1). Train discriminator to clasify actual images against images generated by (untrained) generator
 - (2). Train generator to generate images that fool discriminator into believing they're real.

repeat (1) and then (2) again.

This cycle continues. This is why it's called ADVERSARIAL. it is as if they are competing against each other.

