

April 14, 2023

DSML: Computer Vision.

Generative models and GANs.

Class starts
@ 9:05 pm.



What normal people see
when they walk on street



What Computer Vision
folks see



WHO WOULD WIN?



STATE OF THE ART
NEURAL NETWORK



ONE NOISY BOI

Recap:

$$[\begin{matrix} 0.001 \\ 0.009 \\ 0.9 \\ 0.09 \end{matrix}]$$

Image Classification

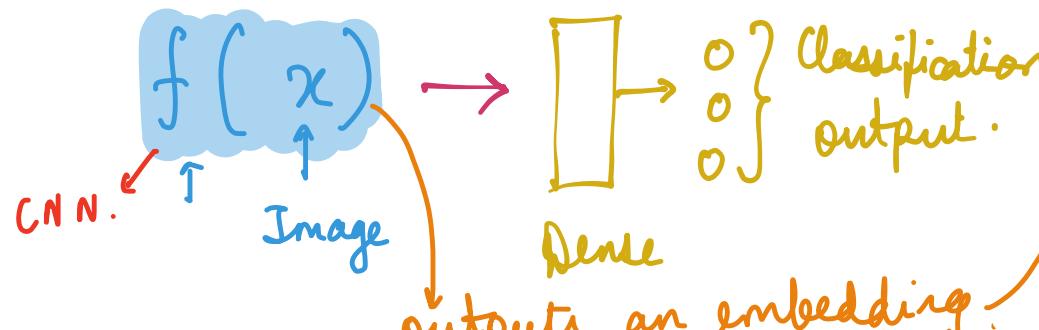
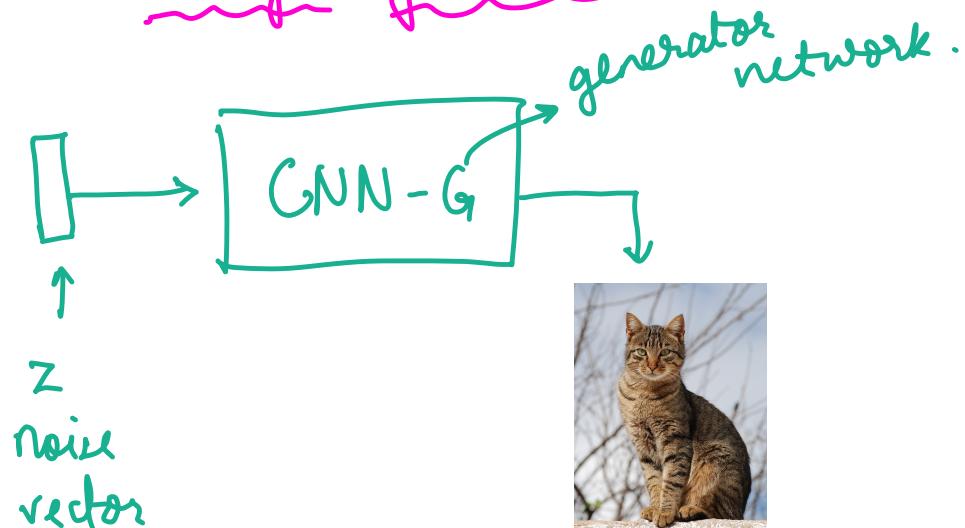
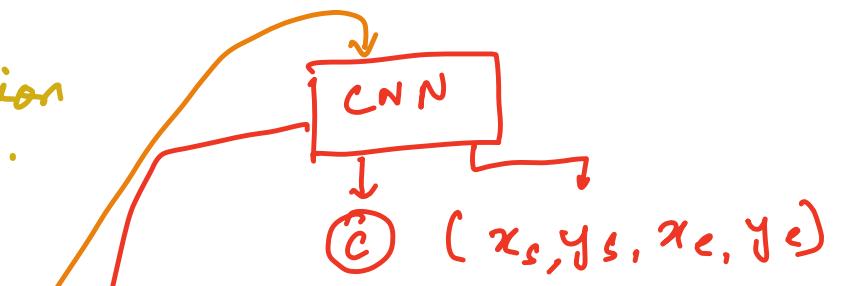


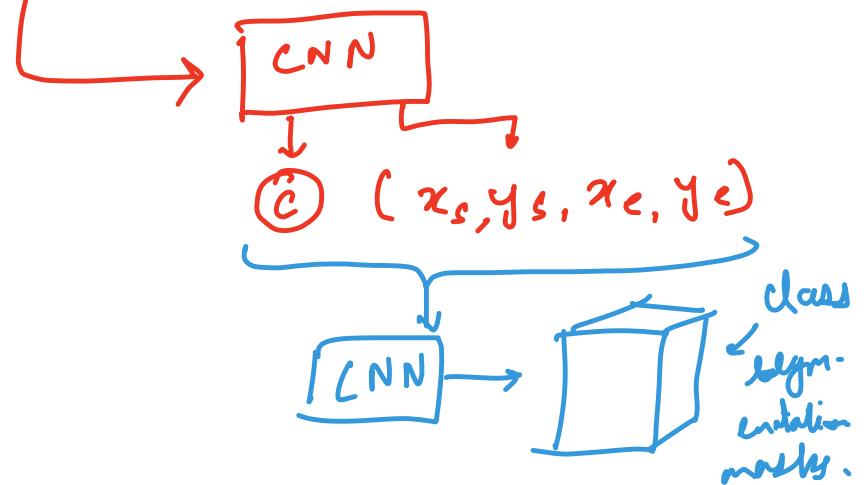
Image Generation



Object Detection



Object Segmentation



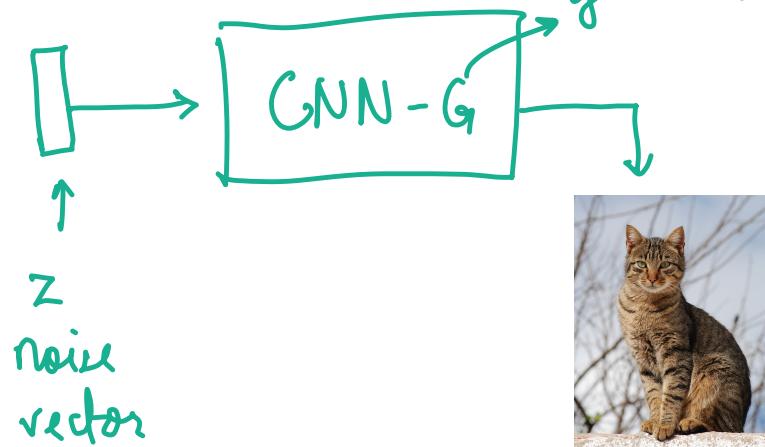
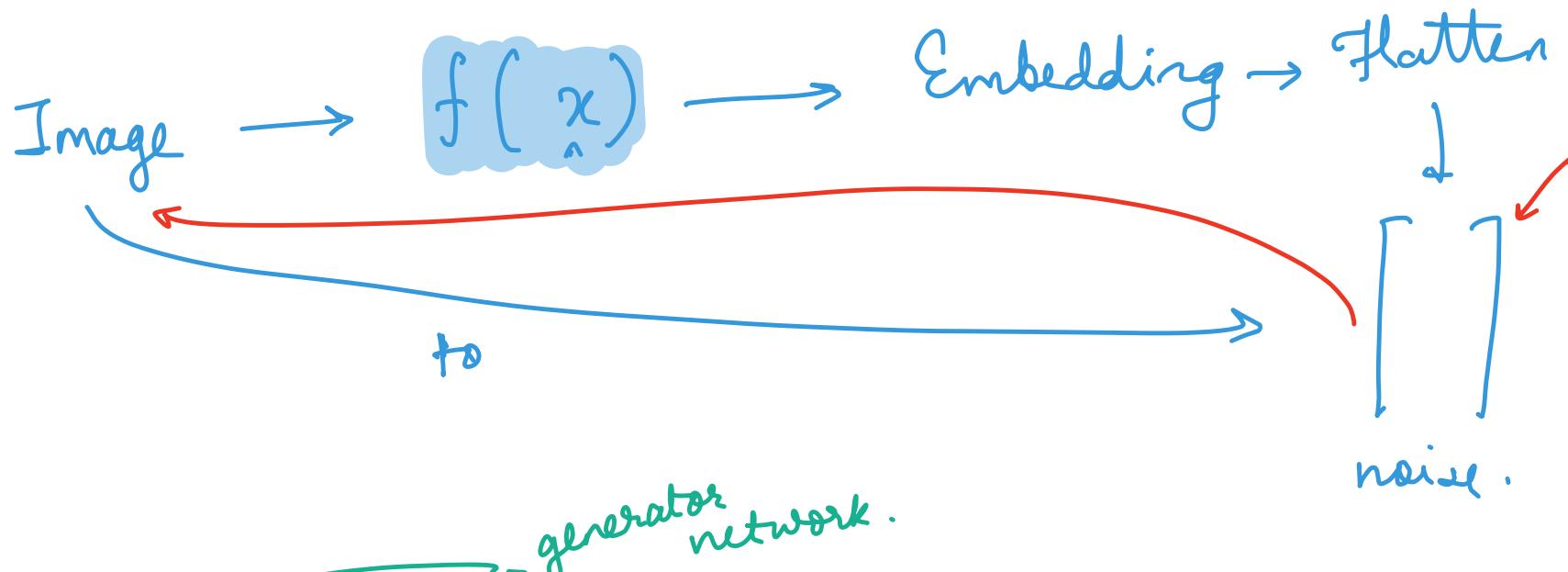


Image Generation is like trying to find an inverse for $f(x)$.

Discriminative vs. generative models.

A model / algorithm which performs Image Classification.

Tries to find the reverse mapping.

$$\{x, y\} \rightarrow \text{labelled Dataset}.$$

$x_i \quad y_i$

$$P(x | y).$$

$$P(y | x_i)$$

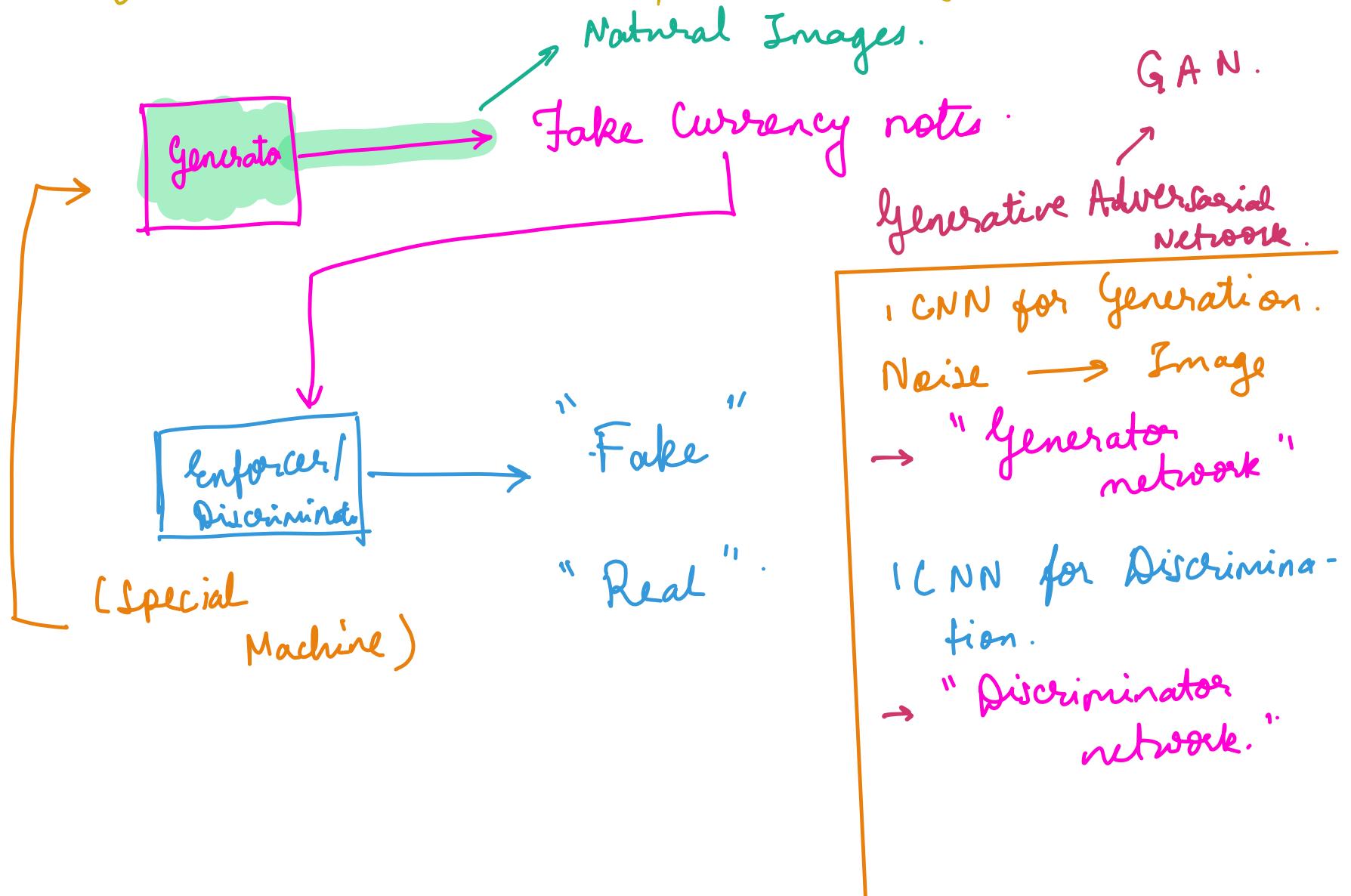
What is learnt? Decision Boundary.

CNN, Decision trees,
SVMs, Regression etc.

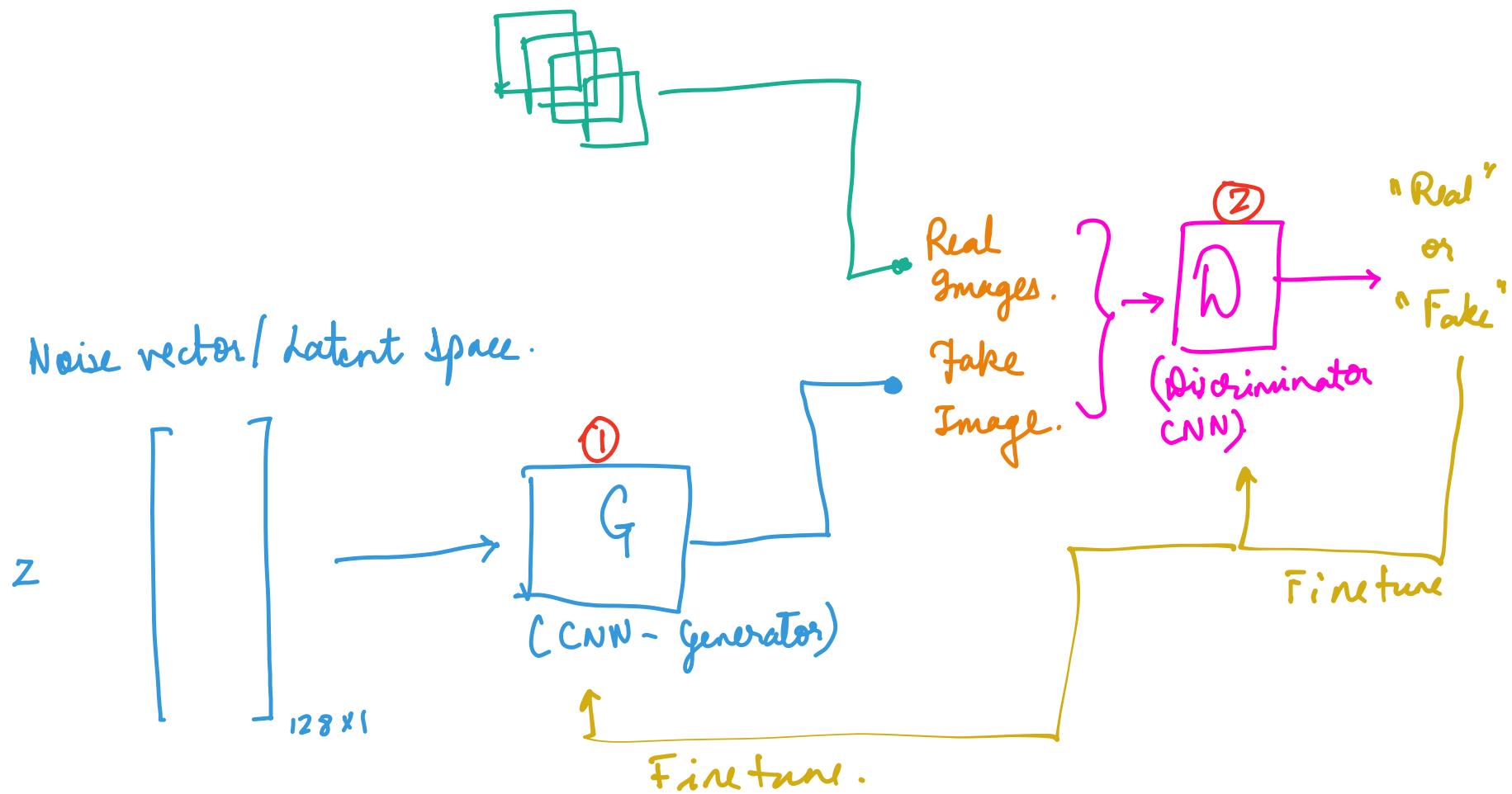
Underlying probability distribution of the Image space.

Intuition behind training a generative model.

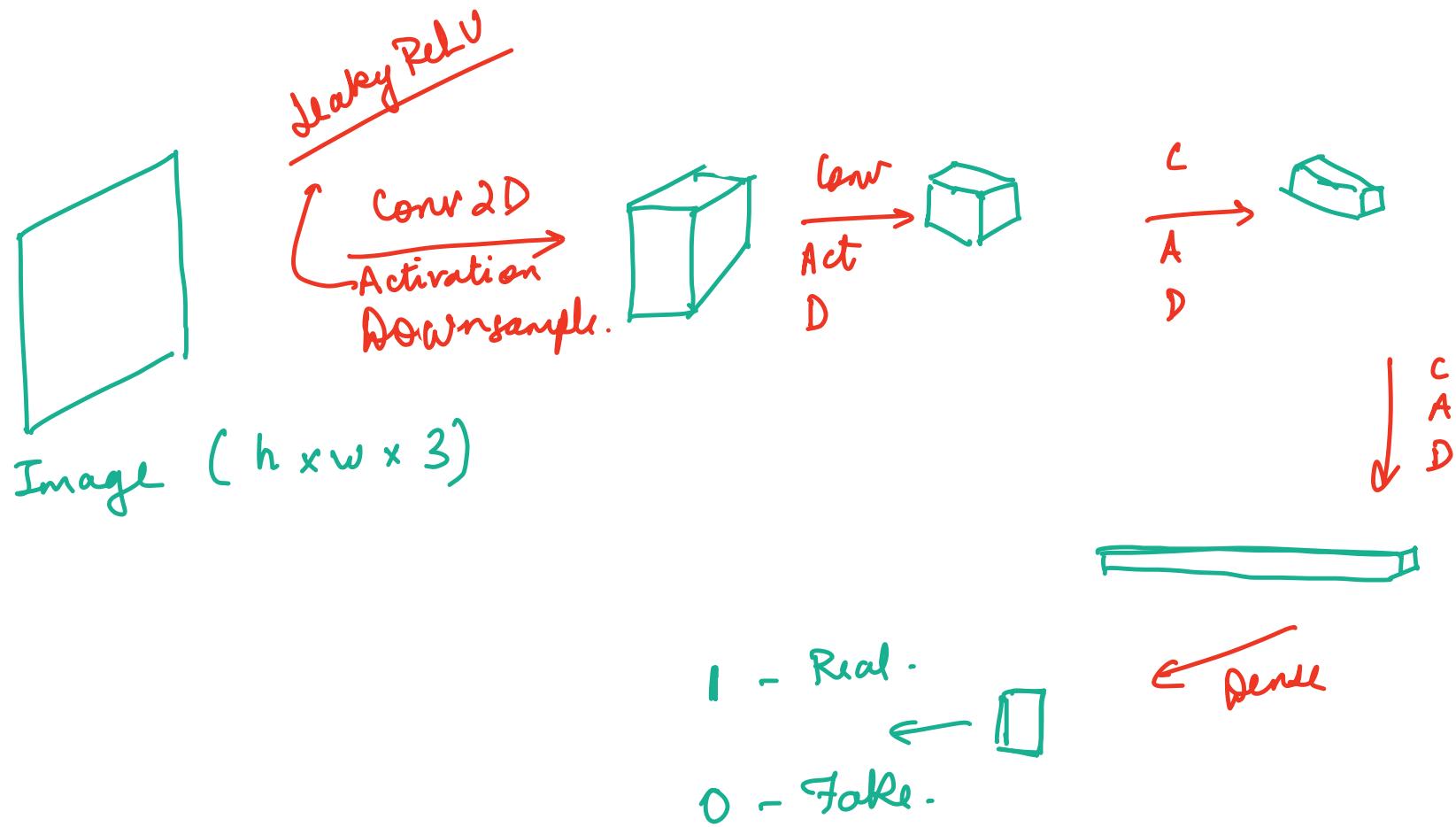
Think about counterfeit currency notes.



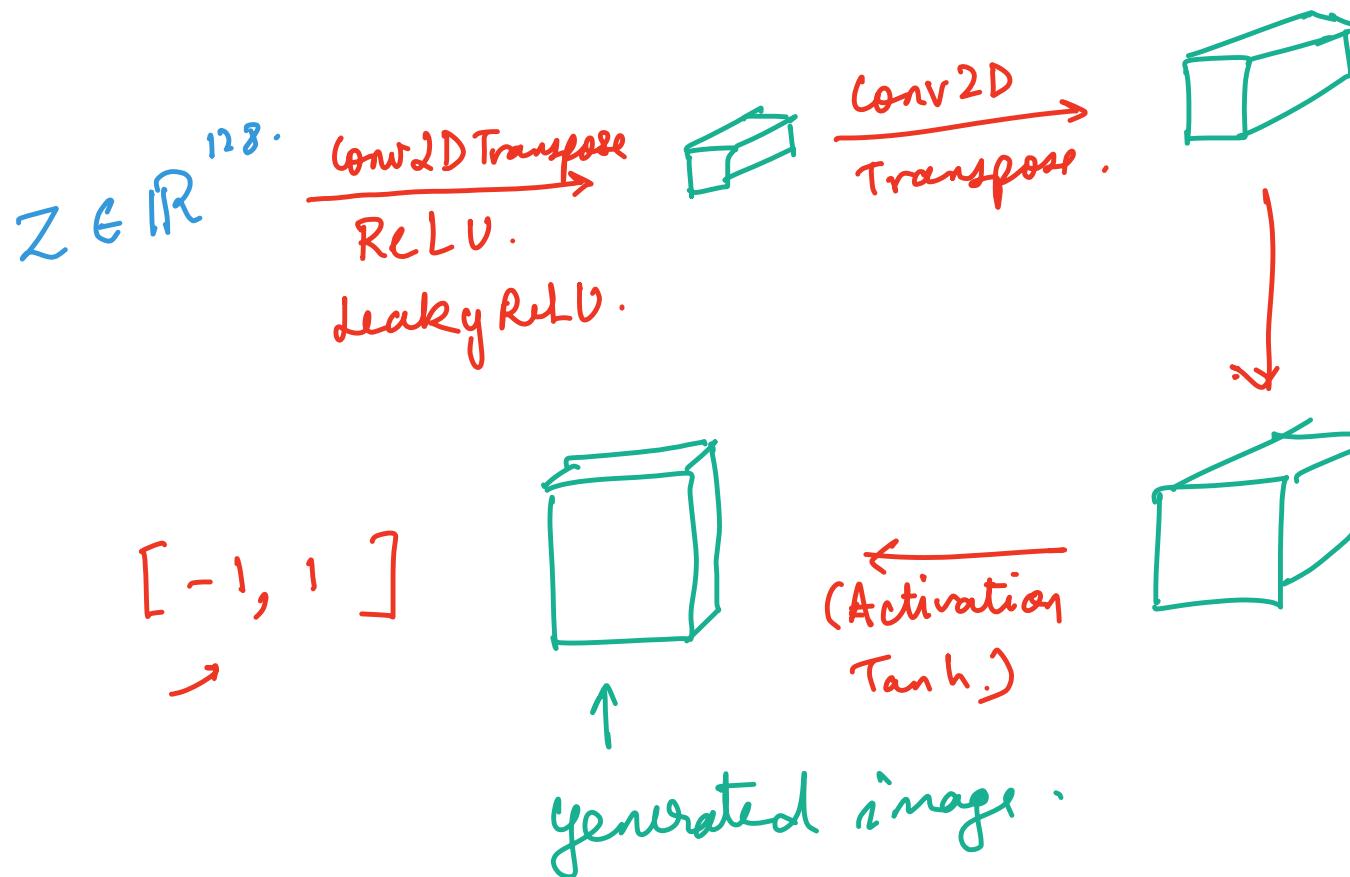
Architecture of a generative adversarial network.



Discriminator Architecture



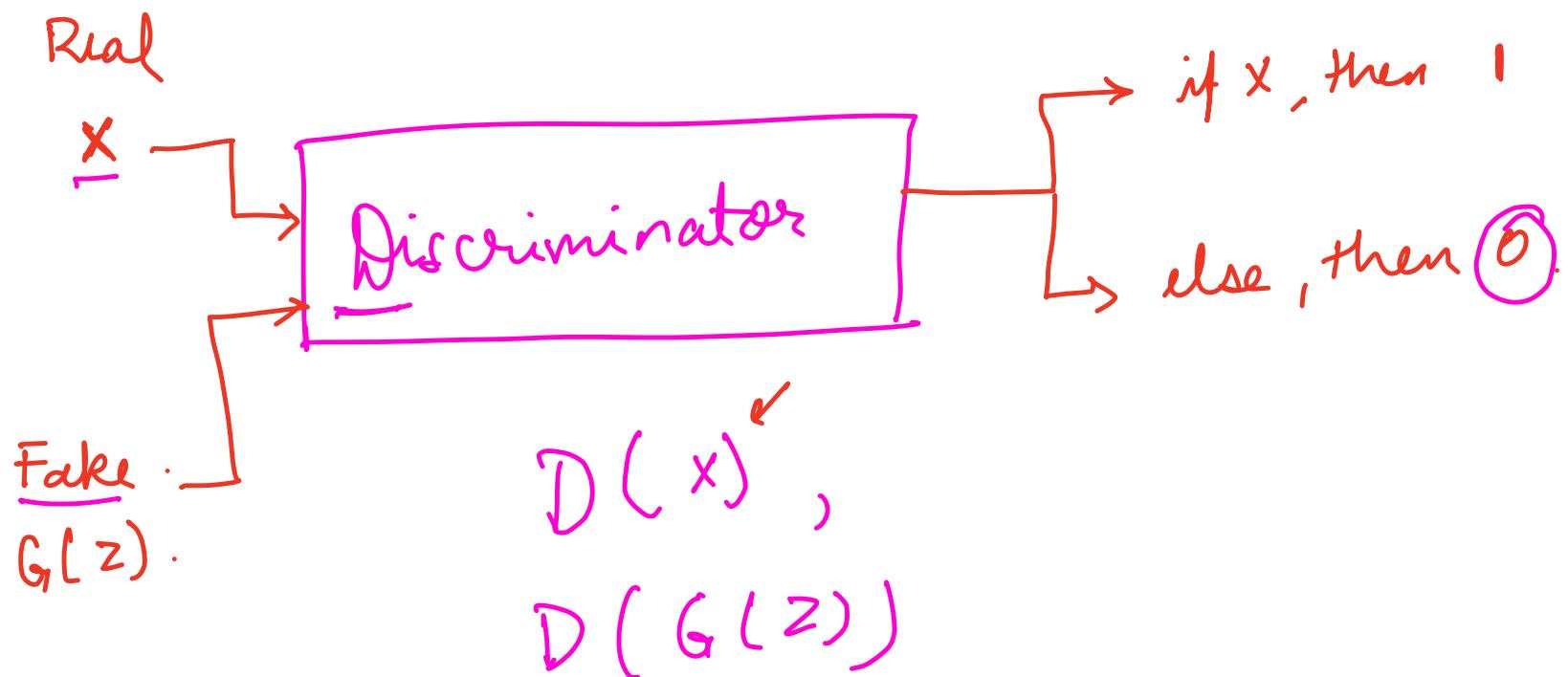
generator Architecture

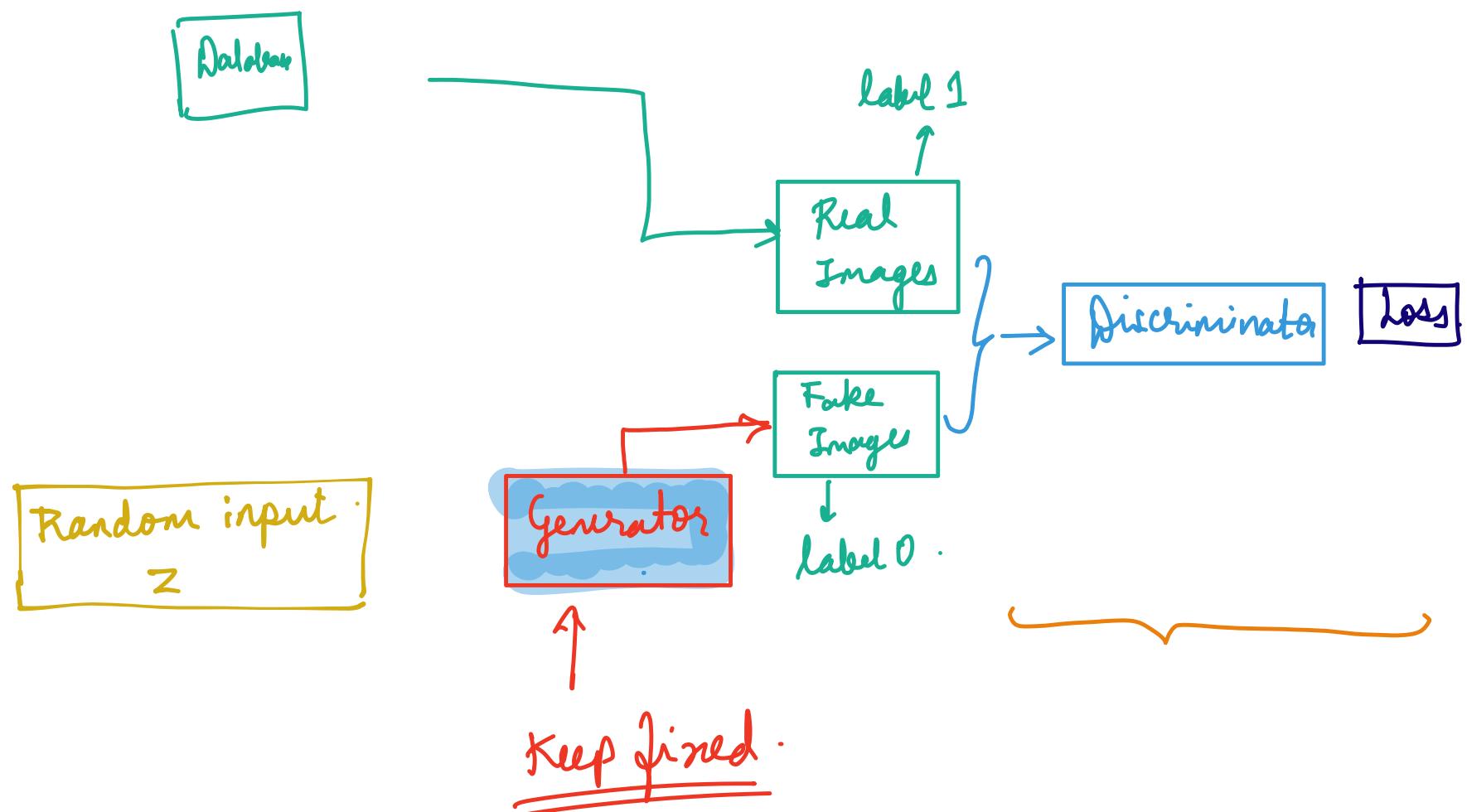


Training a GAN: The GAN loss function.

Binary Cross-Entropy: $N \rightarrow \text{size of dataset}$.

$$-\frac{1}{N} \sum_{i=1}^N \left[y_i \cdot \log(D(x)) + (1-y_i) \log(1-D(G(z))) \right]$$

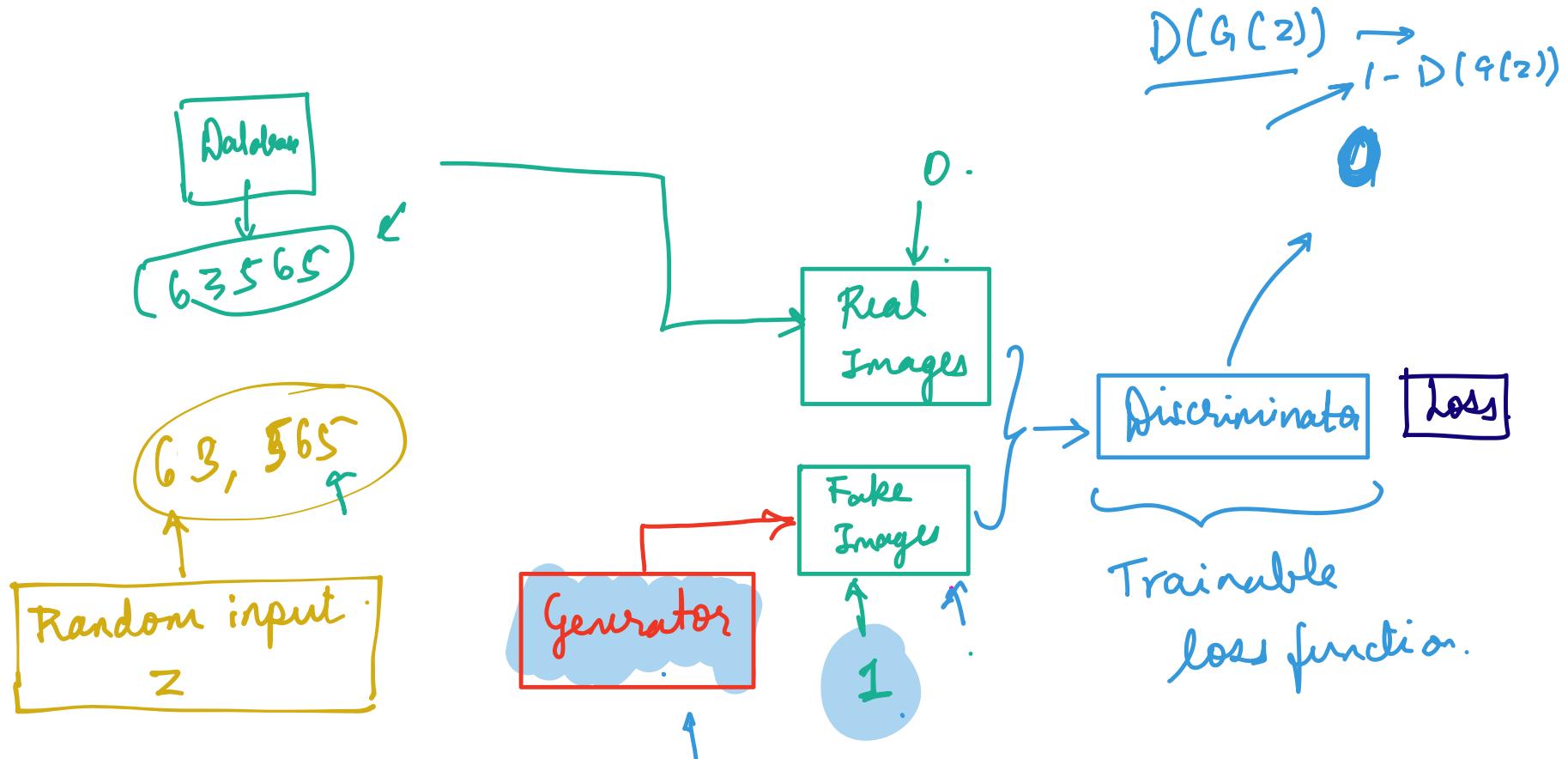




If the input is real, loss : $\max_D \log(D(x))$

If the input is fake, loss : $\max_D \log(1 - D(G(z)))$

Overall :

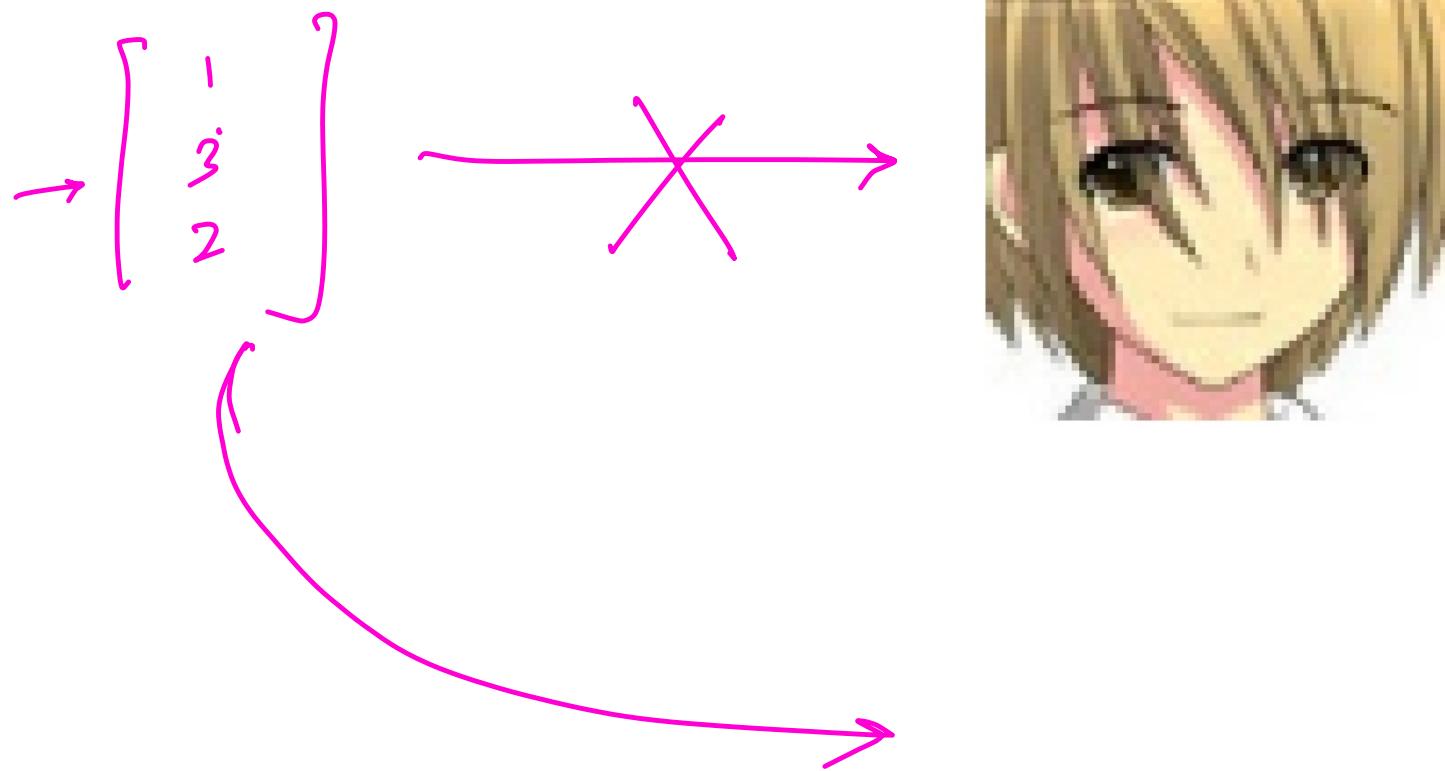


$$\min_G \{ D(G(z), 1) = 1 \cdot \log(1 - D(G(z))) \}$$

$$(1-1) \cdot \log(D(G(z)))$$

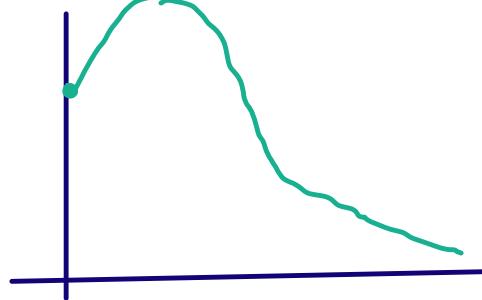
$$\min_G \{ \log(1 - D(G(z))) \}$$

Fine mapping

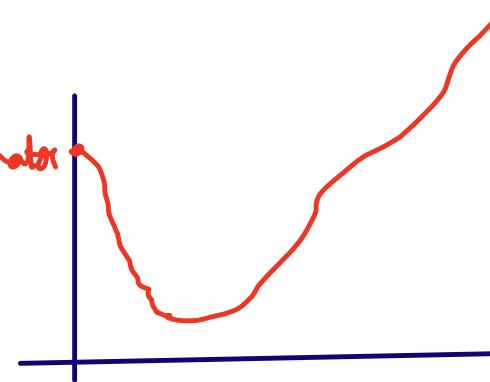


good GAN training

generator loss

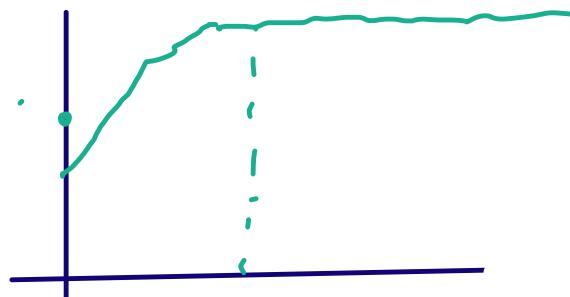


Discriminator loss.



Bad GAN training.

generator loss.



Discriminator loss.

