INDIAN INSTITUTE OF TECHNOLOGY ROORKEE



Generative Adversarial Text to Image Synthesis

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Objective



Translating text in form of single statement human written descriptions directly into image.

this bird has yellow belly breast throat eyebrow with black and grey wings and tail



the blue backed white bellied baby bird has a very fat little belly



this is a very small bird with a white belly and side the bird s head and wings are black

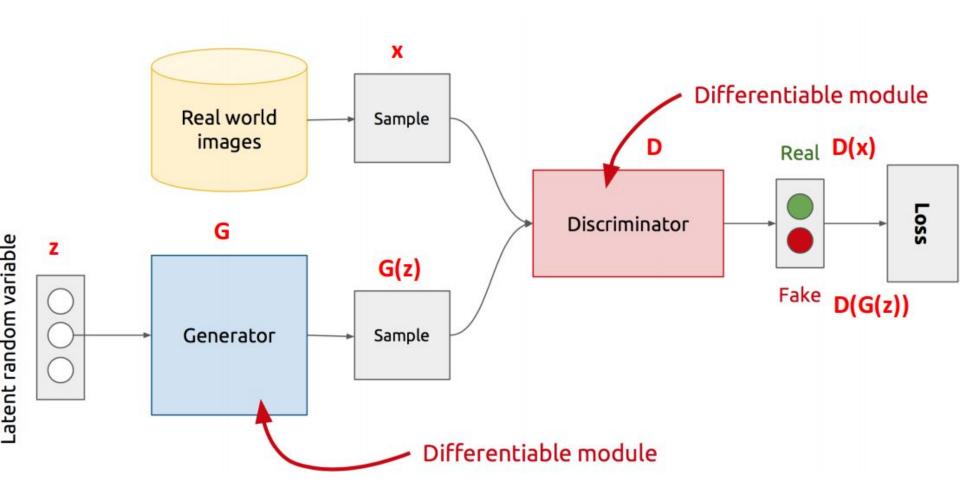






Background: GANs

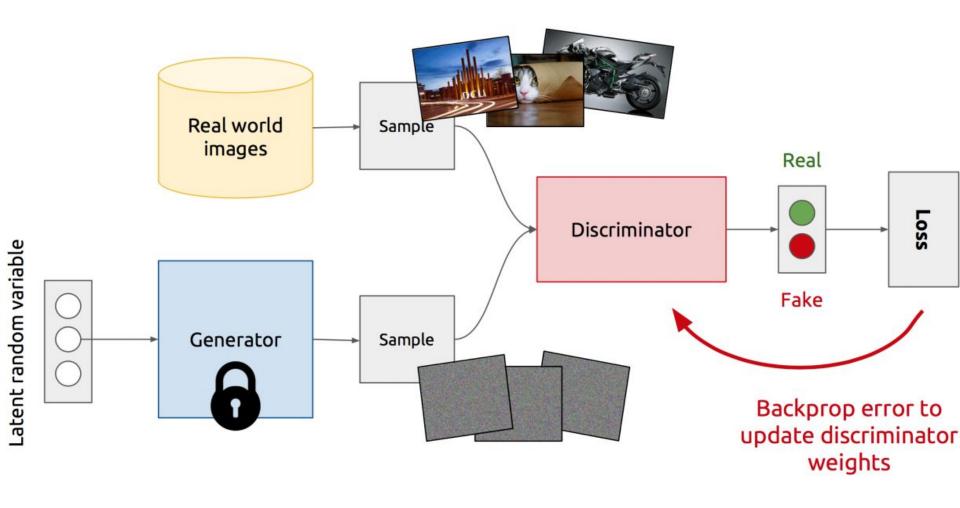




Source: http://slazebni.cs.illinois.edu/spring17/lec11_gan.pdf

Background: GANs (continued)

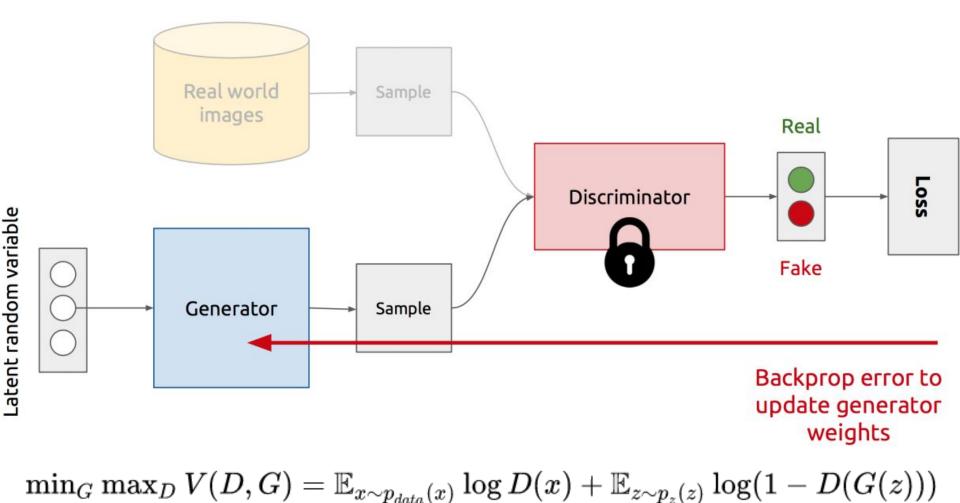




Source: http://slazebni.cs.illinois.edu/spring17/lec11_gan.pdf

Background: GANs (continued)



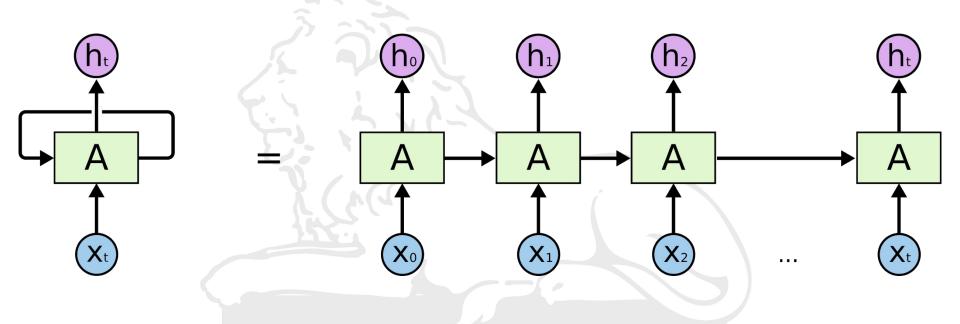


Source: http://slazebni.cs.illinois.edu/spring17/lec11_gan.pdf

Background: Text Embedding



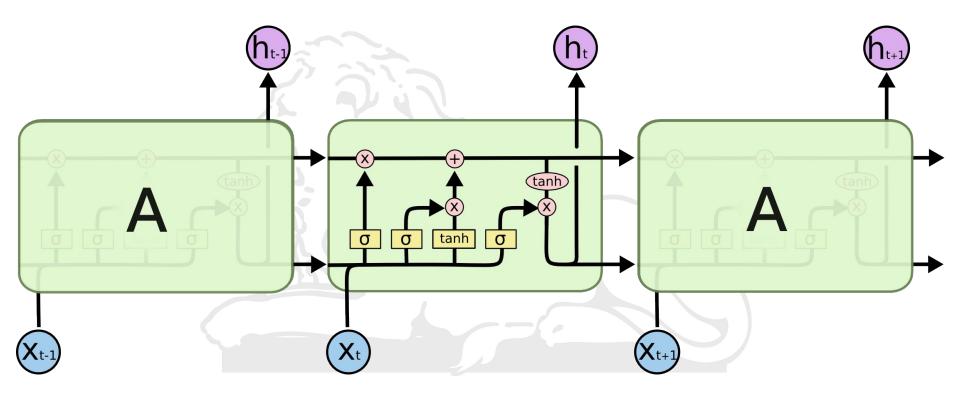
Recurrent Neural Network



Background: Text Embedding (continued)



Long Short Term Memory Network



Background: Text Embedding (continued)



- Skip-thought Vectors :
 - Consists of an encoder-decoder model which generates the surrounding sentences based on the given sentence.
- The following objective function is to be optimized.

$$\sum_{t} log P(w_{i+1}^{t}|w_{i+1}^{< t},h_{i}) + \sum_{t} log P(w_{i-1}^{t}|w_{i-1}^{< t},h_{i})$$





Datasets



We used Caltech-UCSD Birds(CUB) dataset and Oxford-102 flowers dataset.

- CUB dataset contains 11,788 birds images of 200 categories.
- Oxford-102 dataset contains 8,189 images from 102-different flower categories.

CUB	Train	Test
#samples	8,855	2,933
caption/images	10	10

Oxford-102	Train	Test
#classes	82	20
#samples	6,142	2,047
caption/images	5	5



Methodology and Results

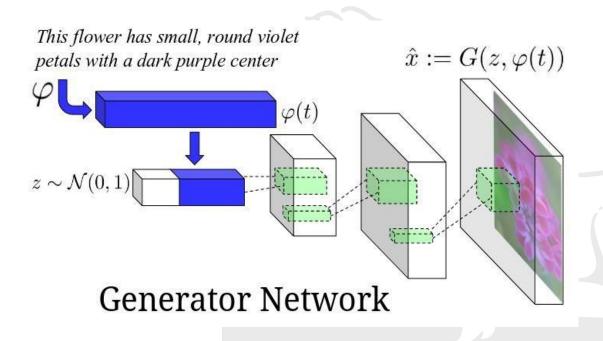
Vanilla GANs







 $s_f \leftarrow D(\hat{x}, h)$ fake image, right text



$$L_g \leftarrow log(s_f)$$

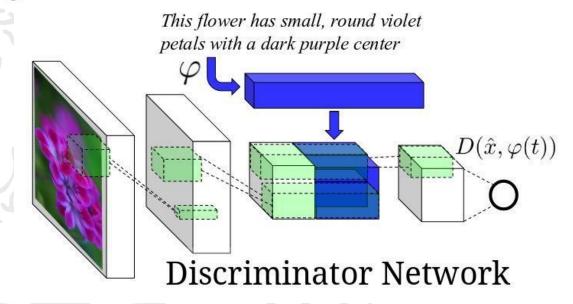
Source: [1]



 $s_r \leftarrow D(x, h)$ real image, right text

 $s_w \leftarrow D(x, \hat{h})$ real image, wrong text

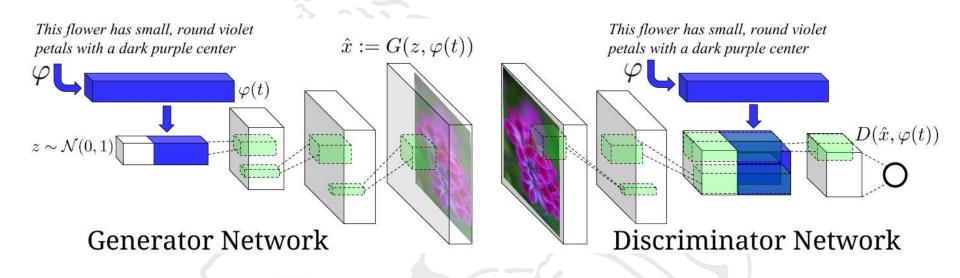
 $s_f \leftarrow D(\hat{x}, h)$ fake image, right text



$$L_d \leftarrow log(s_r) + (log(1-s_w) - log(1-s_f))/2$$

Source: [1]





$$\min_{G} \max_{D} V(D,G) = \mathbb{E}_{x \sim p_{data}(x)} \log D(x|c) + \mathbb{E}_{z \sim p_z(z)} \log (1 - D(G(z|c)))$$

Source: [1]



the flower has abundance of yellow petals and brown anthers



flower is purple and pink in petal and features a dark dense core



this flower has petals that are red and bunched together



the petals of this flower are white and the pistil is a golden yellow



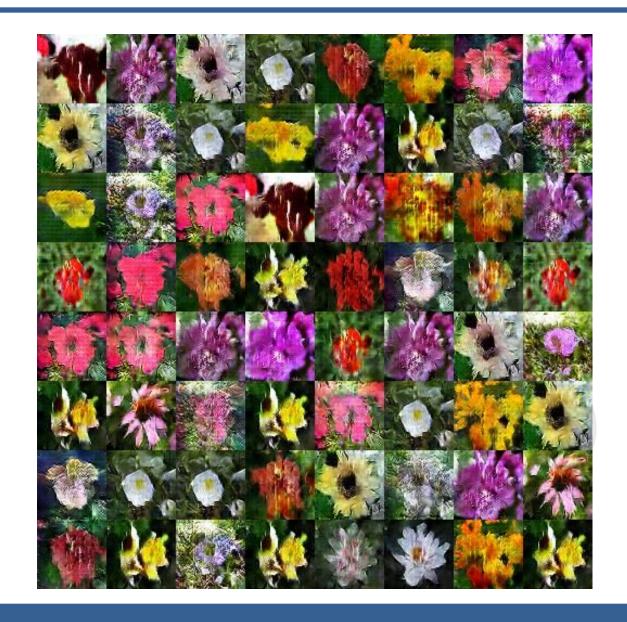
the petals of the flower are pink in color and have a yellow center



this flower is yellow in color, and has petals that are uneven along the edge







WGANs



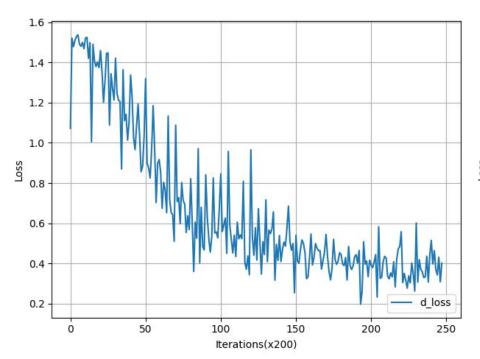
- Minimize the distance between real distribution and model distribution.
- Uses Earth-Mover or Wasserstein distance.
- We want to model a distribution P_{θ} as a generator network g dependent on parameter θ .

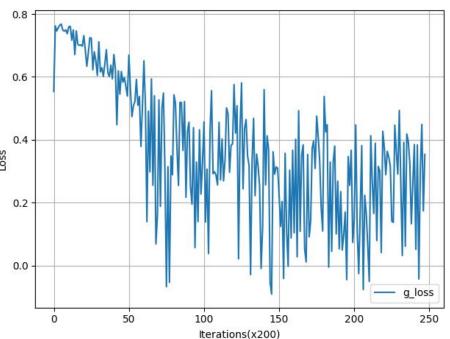
$$egin{aligned}
abla_{ heta}W(P_r,P_{ heta}) &=
abla_{ heta}(\mathbb{E}_{x\sim p_r}[f_w(x)] + \mathbb{E}_{z\sim p_z}[f_w(g_{ heta}(z))]) \ &= -\mathbb{E}_{z\sim p_z}[
abla_{ heta}f_w(g_{ heta}(z))] \end{aligned}$$

where f_w is the critic.

WGANs (continued)







Wasserstein Loss

Generator Loss

WGANs (continued)



grey and lemon colored bird with black cheek patch.



this bird has a black crown as well as a green belly.



this beautiful gold and gray colored bird had a sharp pointed beak and black tail



this bird has a belly that is black with orange cheek patches



a fluffy bird with shades of browns and grays and a speck on white on it's tail.



a brown and gray bird with a short bill and an orange spot on it's crown.



a beautiful bird with black and white wings and a red head with a sharp pointy bill.



WGANs (continued)

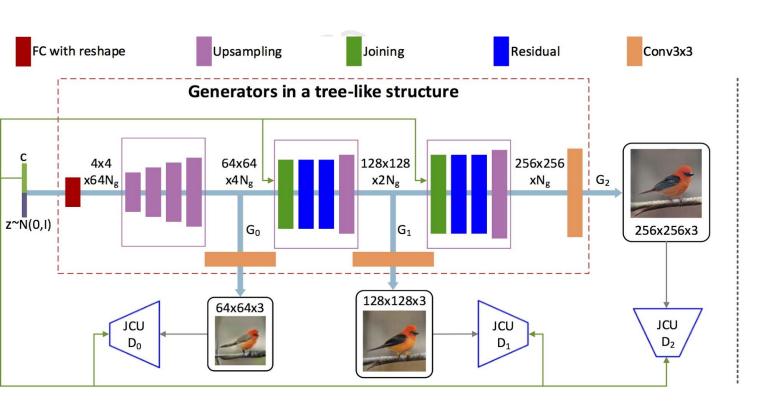


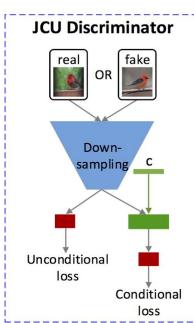


Attention GANs



StackGAN: A multi stage generation process.



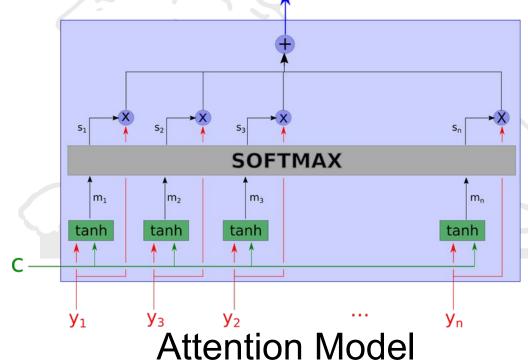


Source: [3]

Attention GANs : Attention Mechanism



- Motivated by the human tendency to focus on certain words.
- Model takes n inputs along with context and returns a weighted sum of inputs.
- Focus on the contextual information.





Deep Attentional Multimodal Similarity Model (DAMSM)

- Text Encoder:
 - uses bi-directional LSTM to extract feature vectors
 - Global sentence vector is generated in the last state.
- Image Encoder:
 - uses part of Inception-v3 trained on ImageNet.
 - Global feature vector is taken from last pooling layer.
- DAMSM loss calculated to find similarity between image and sentence.



Attention Generative Network

- Model has m generator discriminator pairs.
- Each generator takes hidden state h_i as input and produces an intermediary image.

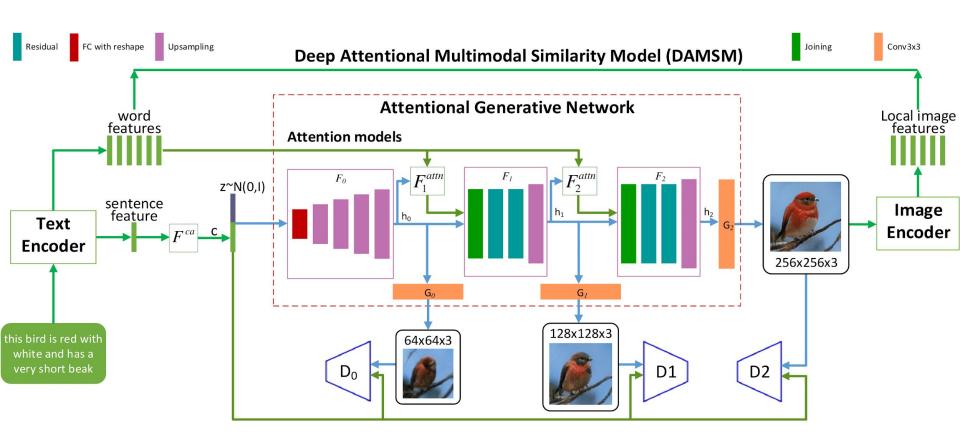
$$\hat{x}_i = G_i(h_i)$$

Hidden states are defined as follows:

$$h_0 = F_0(z,F^{ca}(ar{e}))$$
 $h_i = F_i(h_{i-1},F_i^{attn}(e,h_{i-1}))$ for $i=1,2,\ldots,m-1$

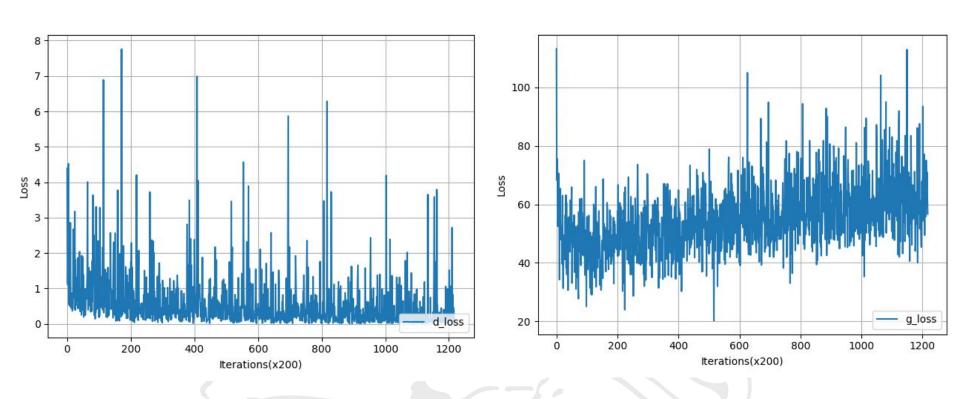
 The word context vectors from attention mechanism is used to generate images for next stage.





Source: [4]



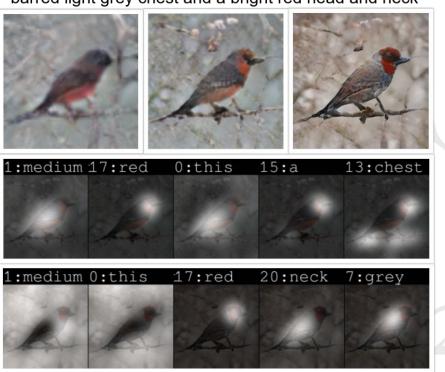


Discriminator Loss

Generator Loss



this medium sized perching bird has a grey body with barred light grey chest and a bright red head and neck

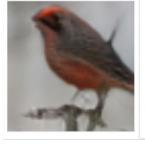


this bird has wings that are blue and has a white belly





This large bird is mostly grey with a long hooked bill



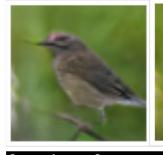








a long biled bird with a red head and white neck and upper belly













this bird has a white breast belly and abdomen and a long black and white

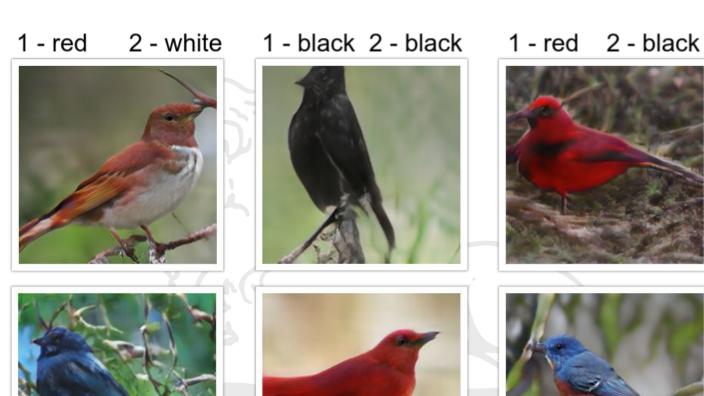


the head is grey with a black crown and throat the body is brown with flecks of red





this bird has wings that are 1 and has a 2 belly



- black









2 - blue

1 - blue

2 - red





Future Scope of Research



- Divide the image generation process into individual object generation.
- WGAN with attention mechanism.
- Training on MS-COCO dataset to produce generalized images.
- Object oriented learning.

Conclusions



- Successfully implemented a model for synthesizing images using text descriptions.
- Generated images of size 256 × 256 and photorealistic quality.
- Implemented image-word loss, DAMSM, to be used for training the model.
- Explored conditional WGAN.

References



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- 5. I. J. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. C. Courville, and Y. Bengio, "Generative adversarial nets," in NIPS, 2014.

Thank You