

Text To Image Using DCGAN

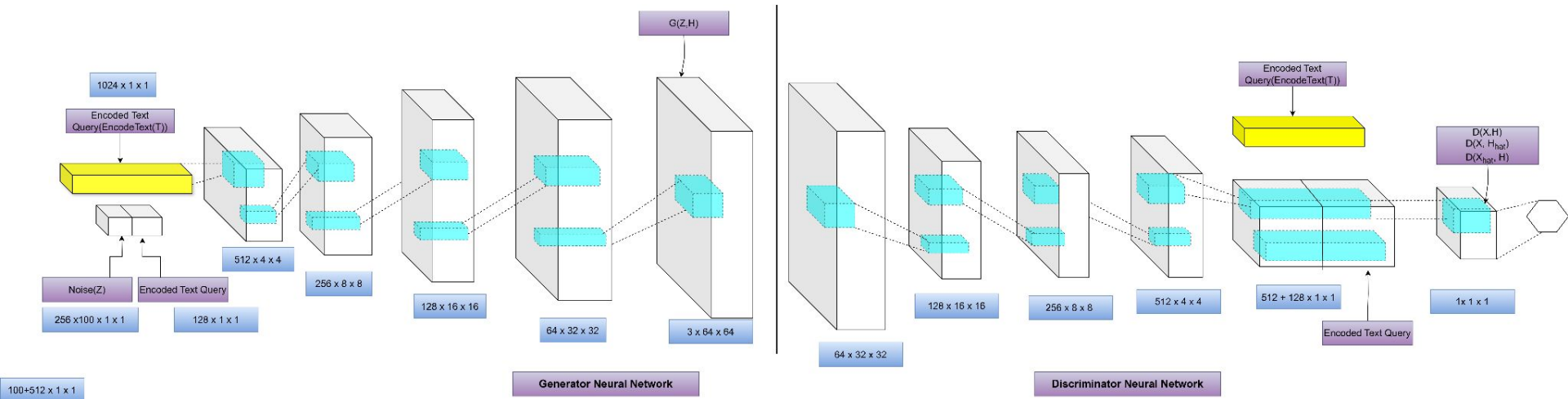
Input

Preprocessed images with embeddings in h5py format

Output

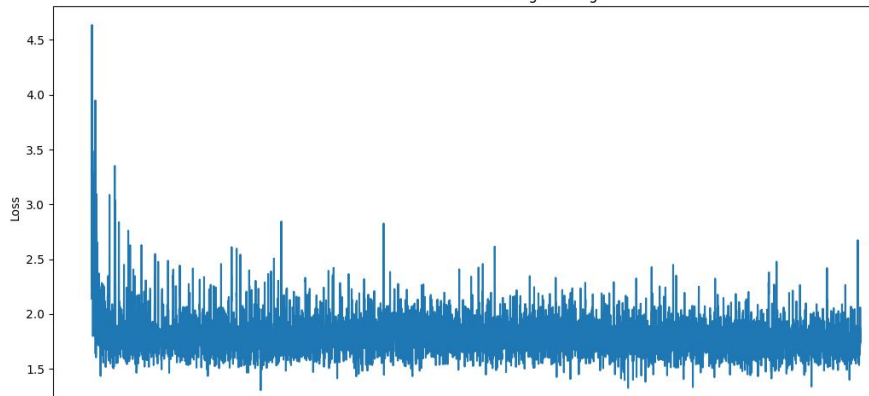
Generate images of flower that match the description present in embeddings

Architecture

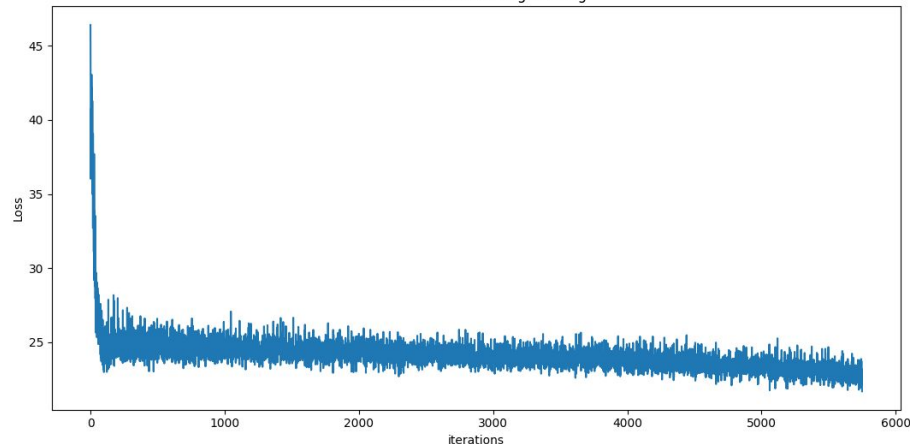


Algorithm & Graphs

Discriminator Loss During Training



Generator Loss During Training



Algorithm : GAN Training For Text-to-Image Generation

Input: Image batch X , matching text T , mismatching text T_{hat} , batch size B , learning rate η

Output: Trained generator and discriminator

- 1: **for** $n = 1$ **to** B **do**
 - 2: **Encode** matching text: $H \leftarrow \text{EncodeText}(T)$
 - 3: **Encode** mismatching text: $H_{\text{hat}} \leftarrow \text{EncodeText}(T_{\text{hat}})$
 - 4: **Generate** noise: $Z \sim \text{Gaussian}(0, I)$
 - 5: **Generate** fake images: $G(Z, H)$
 - 6: **Compute** discriminator scores: $D(X, H)$ (real image with correct text)
 - 7: **Compute** discriminator scores: $D(X, H_{\text{hat}})$ (real image with incorrect text)
 - 8: **Compute** discriminator scores: $D(X_{\text{hat}}, H)$ (fake image with correct text)
 - 9: **Compute** discriminator loss: $L_D \leftarrow \log(D(X, H)) + (\log(1 - D(X_{\text{hat}}, H)) + \log(1 - D(X, H_{\text{hat}})))/2$
 - 10: **Update** discriminator parameters: $\rho_D \leftarrow \rho_D - \eta \cdot \frac{\partial L_D}{\partial \rho_D}$
 - 11: **Compute** generator loss: $L_G \leftarrow \log(D(X_{\text{hat}}, H))$
 - 12: **Update** generator parameters: $\rho_G \leftarrow \rho_G - \eta \cdot \frac{\partial L_G}{\partial \rho_G}$
 - 13: **end for**
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Reference : Generative Adversarial Text to Image
Synthesis by REEDSCOT1, AKATA2, XCYAN1, LLAJAN1
SCHIELE2, HONGLAK