TEXT-TO-IMAGE GENERATION

Final Delivery

Text To Image Synthesis Using DC-GAN

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Abstract

A picture is worth a thousand words!". What if we can generate a realistic image from its description? In recent years, a lot of research and interest focused on text-to-image generation using GANs. In this work, we illustrate the problem and the data we used, build on a work from literature, then state the conclusions and possible future works.

Introduction

Text-to-image generation is to translate text in the form of human-written description into an image that is indistinguishable from realistic one. Examples of input/output are provided below.

Text-to-image generation has many practical and useful applications including, but not limited to:

Computer-aided tools
Language learning
Literacy development
Storytelling
Art generation

Examples of input/output

A flower with long pink petals and raised orange stamen.

A sheep standing in an open grass field.

Methodology

Tackling this problem requires learning a text feature representation that captures the important visual details (Natural Language Representation), then using these features to synthesize a pseudo-real image (Image Synthesis). With the advances in Deep Learning, the two areas have evolved and new methods are introduced, particularly using generative adversarial networks (GANs).

The work of Reed et. al (2016) used deep convolutional generative adversarial network (DC-GAN) conditioned on text features encoded by a hybrid character-level convolutional recurrent neural network. The architecture is shown below. We build on this architecture (in Tensorflow).

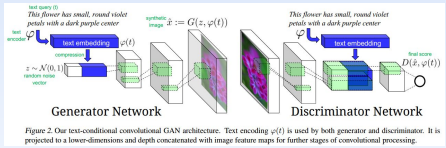


Figure 2. Our text-conditional convolutional GAN architecture. Text encoding $\varphi(t)$ is used by both generator and discriminator. It is projected to a lower-dimensions and depth concatenated with image feature maps for further stages of convolutional processing.

Training phase

* Sentence embedding is generated for all the captions
* Sentence embedded vector is fed to the CNN as its condition
* Text-to-image GAN is then trained over the image dataset

Generative phase

* Sentence embedding the required Input caption
* Feed the input caption vector to our trained model

Results

We trained our final model for 200 epochs over **Oxford-102** dataset which contains 102 categories of flowers with 40-258 images each (a total of 8,189 images), along with their text descriptions, we got the following

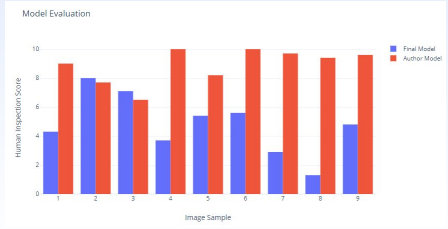
this flower has petals that are yellow, white and purple and has dark lines

this flower has a lot of small round pink petals.

the center is yellow surrounded by wavy dark purple

Evaluation

We evaluated our final model compared with the author's model using average Human Inspection score



Conclusion

* Overall, it is obvious that the author's model is better. This can be due to the learning with manifold interpolation he used (GAN-INT)

* Sent2Vec encoder highly affects the training phase

* The model takes too much time to be trained so it is very hard to make the appropriate hyperparameter tuning and even more harder to change in model architecture.

Future Work

* Using pyTorch instead of Tensorflow to implement
* progressive augmentation
* More better hyperparameters tuning
* Training over CUB-200 birds dataset
* Trying different text encoder

References

Reed, S., Akata, Z., Yan, X., Logeswaran, L., Schiele, B., and Lee, H. (2016b). Generative adversarial text to image synthesis. Proceedings of the International Conference on Machine Learning (ICML).
https://arxiv.org/pdf/1605.05396.pdf

Paarth Neekhara text-to-image implementation in Tensorflow.
https://github.com/paarthneekhara/text-to-image

Oxford 102-flowers dataset.
https://www.robots.ox.ac.uk/~vgg/data/flowers/102/

Jamie Kiros skip-thoughts.
https://github.com/ryankiros/skip-thoughts#getting-started

Generative Models, CS231n Stanford course. Available:
http://cs231n.stanford.edu/slides/2019/cs231n_2019_lecture11.pdf

1. PROBLEM STATEMENT

2. RELATED WORK

3. CONTRIBUTION

4. EXPERIMENTAL RESULTS

5. CONCLUSION

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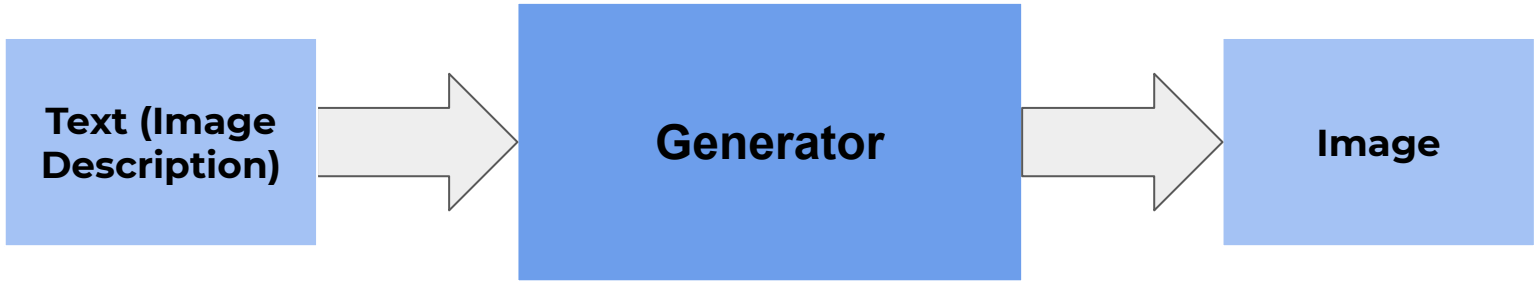
PROBLEM STATEMENT

Problem

Translate text in the form of human-written description into image that is indistinguishable from realistic one



Examples[1]

a flower with long pink petals and raised orange stamen.

a sheep standing in an open grass field.

2 RELATED WORK

DC-GAN (Reed et al., 2016)[1]

- Train a DC-GAN conditioned on text features encoded by a hybrid character-level Convolutional RNN

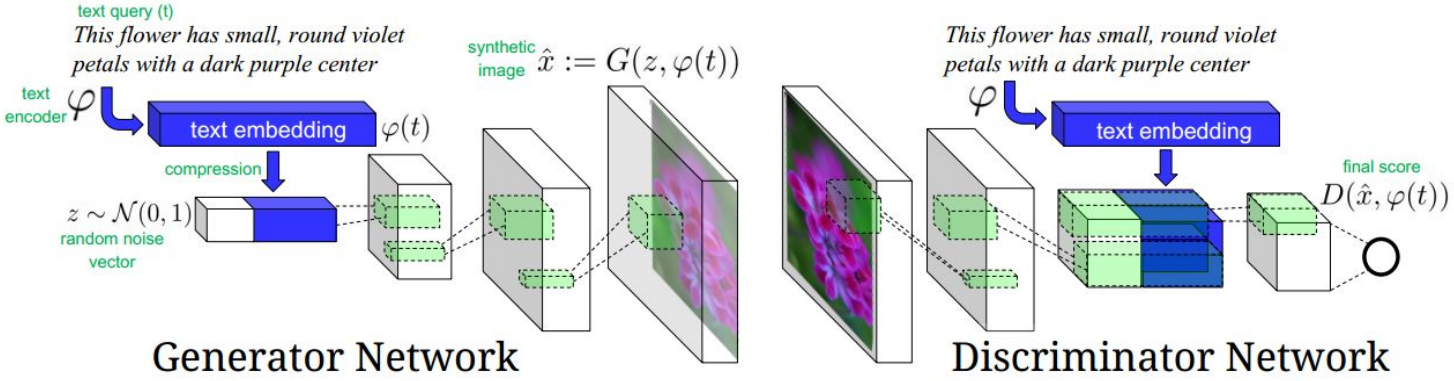


Figure 2. Our text-conditional convolutional GAN architecture. Text encoding $\varphi(t)$ is used by both generator and discriminator. It is projected to a lower-dimensions and depth concatenated with image feature maps for further stages of convolutional processing.

Original (pre-trained) model

- Implementation of the paper (by the author) in PyTorch
  - https://github.com/reedscot/icml2016
  - Deployed the pretrained model

this flower has white petals and a yellow stamen

the flower has yellow petals and the center of it is brown

a flower has long purple petals and a yellow stigma

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CONTRIBUTION

Proposed contribution

Build on the architecture of **DC-GAN**[1]

Hyper-parameters

Try to tune to increase performance

Architecture

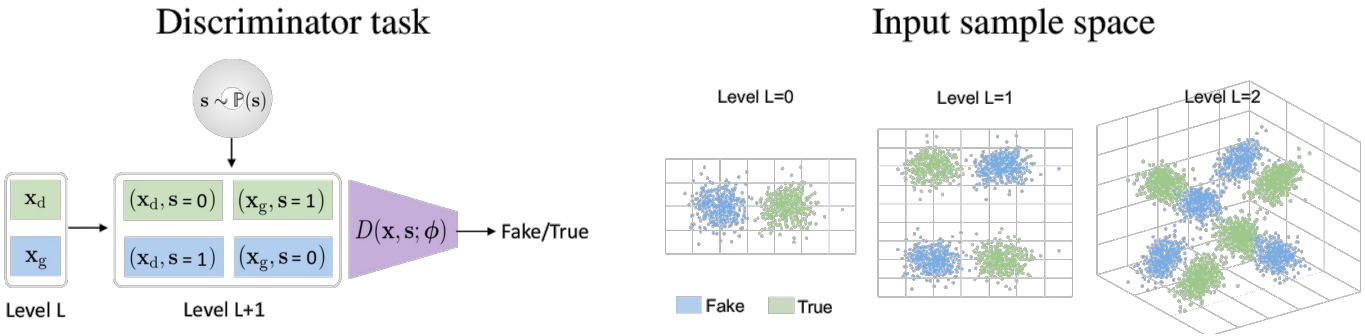
Try to modify (e.g. introduce progressive augmentation)

2-in-one image

Filter COCO dataset to get images with birds and flowers in same text description, then train the model on them

Progressive Augmentation[2]

- **Problem**: the discriminator learning is faster than the generator and this leads to GAN instability
- **Solution**: making harder the learning task of the discriminator by augmenting progressively its input space with an arbitrary random bit sequence, thus enabling continuous learning of the generator



- Implementation: modify the input layer of the discriminator network (Problem)

Training the model

- Building on text-to-image[3] repository (TensorFlow)
- Training over Oxford-102 flowers dataset
- Training phase
  - Sentence embedding is generated through skip-thoughts[4] for all the captions
  - Resulting Sentence embedded vector is fed to the CNN as its condition
  - Text-to-image GAN is then trained over the dataset
- Generative phase
  - Sentence embedding the required Input caption
  - Feed the input caption vector to our trained model

Live Demo 😀

4 Experimental Results

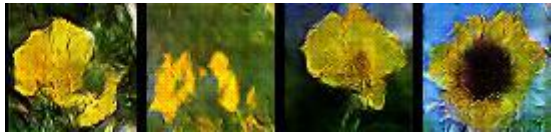
Results

the flower shown has yellow anther red pistil and bright red petals

this flower has petals that are yellow, white and purple and has dark lines

this flower is orange in color, and has petals that are ruffled and rounded

the flower has yellow petals and the center of it is brown

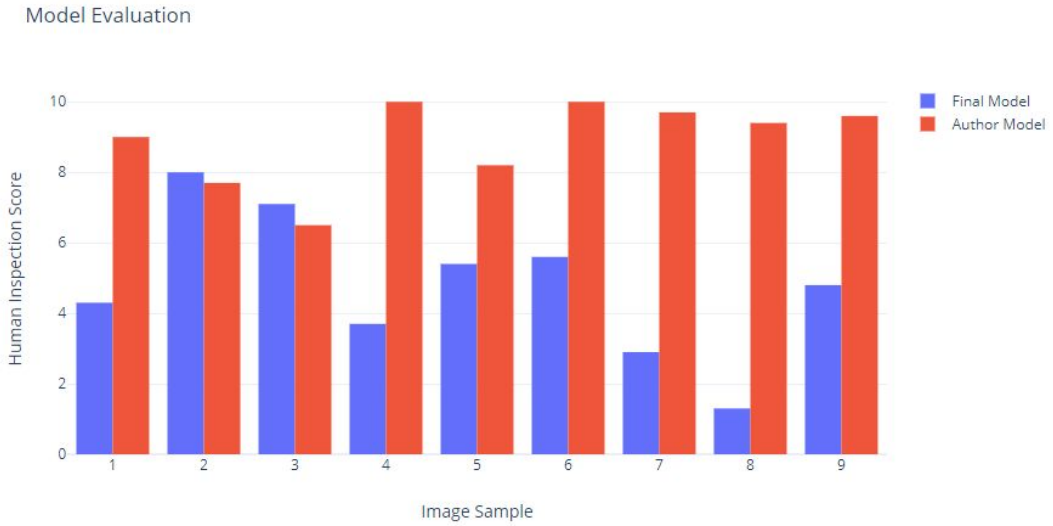


this flower has white petals and a yellow stamen

this flower has lots of small round pink petals

Evaluation

- We used Human-Inception score.
- A set of images is generated using both models. Then some of our colleagues are asked to rate each image using [this evaluation form].



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Conclusion

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- Sent2Vec encoder highly affects the training phase
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Future Work

- Using pyTorch instead of Tensorflow[5] to implement progressive augmentation
- More better hyperparameters tuning
- Training over CUB-200 birds dataset
- Trying different text encoder

Team Members Contribution

Mahmoud Tarek

- Deployed original (pretrained) model to get insights of the generated images
- Solved the practical issues in implementation
- Investigated on how to include PA to the model

Muhammad Sharaf

- Explored the dataset deeply to choose the best chunk of data that minimize the training time
- Trained both models, the Sent2Vec model and Text-to-image model
- Trying different hyper-parameters

References

1. Reed, S., Akata, Z., Yan, X., Logeswaran, L., Schiele, B., and Lee, H. (2016b). Generative adversarial text to image synthesis. Proceedings of the International Conference on Machine Learning (ICML). Available: https://arxiv.org/pdf/1605.05396.pdf
2. Zhang, Dan & Khoreva, Anna. (2019). PA-GAN: Improving GAN Training by Progressive Augmentation. Available: https://arxiv.org/pdf/1901.10422.pdf
3. text-to-image implementation in Tensorflow by Paarth Neekhara . https://github.com/paarthneekhara/text-to-image
4. Oxford 102-flowers dataset. https://www.robots.ox.ac.uk/~vgg/data/flowers/102/
5. Sent2Vec encoder implementation “Skip-Thought Vectors”. https://github.com/ryankiros/skip-thoughts

OUR TEAM

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Thanks!