

UNDERSTANDING AND IMPLEMENTING GENERATIVE ADVERSARIAL NETWORKS (GANs): ONE OF THE BIGGEST BREAKTHROUGHS IN THE DEEP LEARNING REVOLUTION

PyConThailand | 2019



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About Me

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- Currently, working as a Platform Software Engineer at Bigbasket, India (India's largest online food and grocery store).
- MSc in Advanced Computing (Machine Learning, Artificial Intelligence, Robotics, Cloud Computing, and Computational Neuroscience) from University of Bristol, United Kingdom.
- International Tech Speaker (spoke at numerous International Conferences like GeoPython, 2018, and EuroPython, 2018, and more).
- Former Software Developer Intern at IBM & an ALL STACK DEVELOPER capable of designing and developing solutions for Mobile, Web, Embedded Systems, and Desktop.
- Represented India at International Hackathons like Hack Junction'16, Finland and Hack the North'16, Canada. Got invited for more than a 'dozen' of prestigious International Hackathons (PennApps'17, HackNY'17, Hack Princeton'17 and many more) and Conferences.
- Microsoft Certified Professional, Microsoft Technology Associate, IBM Certified Web Developer, and Hewlett Packard Certified Developer.
- 8+ International Publications [Latest work got published in ACM CHI 2018. The project was exhibited in Montreal, Canada.].
- Received 6 Honours and Awards (International and National level).

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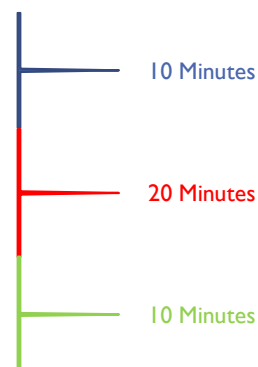
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Flow of the Talk

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- 🔗 A Succinct Prelude to Deep Learning (DL).
- 🔗 A Brief Introduction to Adversarial Training.
- 🔗 Understanding Discriminative and Generative Models.
- 🔗 Working and Architecture of Generative Adversarial Networks (GANs).
- 🔗 Quick Hands-on and Code Walkthrough (using Python).
- 🔗 Tips to Train GANs Better.
- 🔗 Applications of GANs.
- 🔗 Roadmap to Further Study About GANs.
- 🔗 End of Talk followed by Questions and Answers Session.



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Pre-requisites

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- 🔗 Basic understanding of Python language and TensorFlow.
- 🔗 Knowledge of Artificial Neural Networks (better if having experience with Convolutional Neural Networks).
- 🔗 Elementary Linear Algebra, Calculus, and Statistics.

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Introduction to ANNs and DL

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- Artificial Neural Networks (ANNs) are the computing systems that are highly influenced by the biological neural circuits (the neural connections in the brain).
- The neural networks enable a machine to learn patterns from some given observational data and to perform various tasks based on that learning.
- For example, a neural network can help in predicting the future stock prices of a company after being trained with the company's stock prices data of the past few years.
- Deep Learning (DL) is a set of powerful methods that are used for learning in the neural networks.

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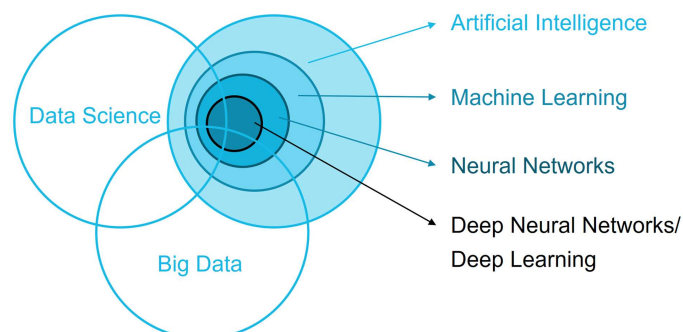
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The Big Picture

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Source: <https://www.fokus.fraunhofer.de/en/fame/workingareas/ai>

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Common Types of Neural Networks

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Some common types of neural networks are stated below:

- Feed Forward Neural Networks.
- Recurrent Neural Networks.
- Convolutional Neural Networks.
- Auto-Encoders.
- Markov Chain Models.
- Boltzmann Machines.
- Generative Adversarial Networks. ✓
- And many more...

The Neural
Network Zoo

Detailed Information: <https://www.asimovinstitute.org/author/fjodorvanveen/>

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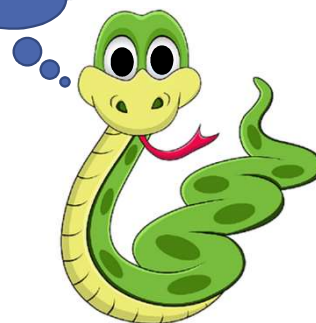
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A BRIEF INTRODUCTION TO ADVERSARIAL TRAINING

The Important
Part Starts...



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Story of a Counterfeiter

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Mary



First Sketch



Mona Lisa

John



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Story Continued...

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Mary



Tenth Sketch



Mona Lisa

John



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Mary Gaining Perfection...

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Mary




Fiftieth Sketch



Mona Lisa

John



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Finally, Mary fooled John

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Mary




Hundredth Sketch



Mona Lisa

John



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Discriminative and Generative Models

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- A Discriminative Model is a supervised learning based model which observes the data and learns to classify the data. These models don't stress much on the data distribution but on the quality of data.
- A Generative Model can be defined as a model (think of it to be like a mathematical representation of a real-world process) that is used to generate data which seems real.
- Generative Models are able to learn mostly any kind of data distribution using unsupervised learning.
- A large amount of data in some domain (like images, audio, sequences) is used for training the generative model and the model learns the underlying data distribution. After learning the data distribution, the model is able to generate the data which looks real.

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- In nutshell, a Discriminative Model models the decision boundary between the classes. On the other hand, a Generative Model models the actual data distribution of each class.
- A Discriminative Model is good at classifying/categorizing the data, whereas, a Generative Model is good at producing very similar data distribution.

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Generative Adversarial Networks

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- Generative Adversarial Networks are formed by combining a Discriminator (network using a Discriminative Model) and a Generator (network using a Generative Model) in form of a network.
- The goal of a GAN is to sample from a simple distribution (say a Normal Distribution) and then learn a complex transformation from simple distribution to the training distribution (training distribution is provided in form of bulk training data).

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Sample Distribution [m dimensional]
 $Z \sim N(0, I)$: Normal Distribution (say)

Generated Sample [n dimensional]

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Training a GAN

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- We use a two players game in order to train a GAN.
- One player is a Generator. The job of the generator is to take a sample distribution (latent space) and through a complex transformation (using a neural network), learn the training distribution i.e. generate a real looking sample.
- Other player is a Discriminator. The job of the discriminator is to get better and better at distinguishing between the "REAL" sample and the "FAKE" sample.
- The generator tries to produce samples that look so natural that the discriminator thinks that the samples came from the real data distribution.
- Try to correlate this scenario with the story of "Mary the Counterfeiter" and "John the Investigator". Mary can be considered as the Generator and John can be considered as the Discriminator.
- GAN training becomes successful when the Discriminator is not able to distinguish between the real and the generated samples. This happens because the Generator learns the training data's distribution very well.

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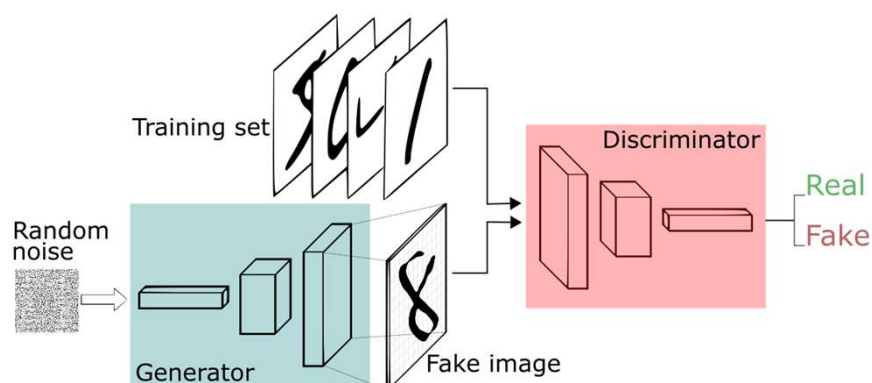
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The Intuition and Setup

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Source: <https://skymind.ai/wiki/generative-adversarial-network-gan>

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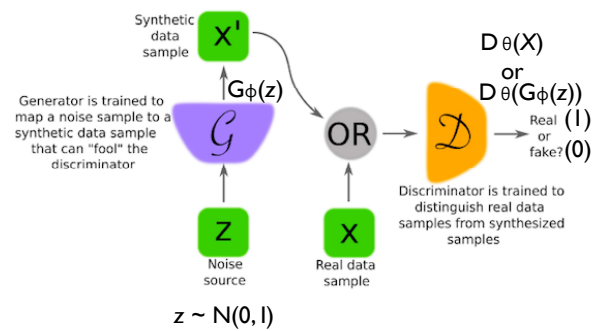
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Diving into Mathematics of GANs

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- Let G_ϕ denote the Generator and D_θ denote the Discriminator. Here, ϕ and θ are the parameters of G and D , respectively.
- The Discriminator assigns its input a score between 0 and 1 \Rightarrow this tells the probability of the sample being real or fake.
- The Generator always wants the score given by the Discriminator to be highest i.e. equal to 1.



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Mathematics of GANs

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- Objective/Cost/Loss function for the Generator is the log likelihood:

$$\text{maximize } \log D_\theta(G_\phi(z))$$

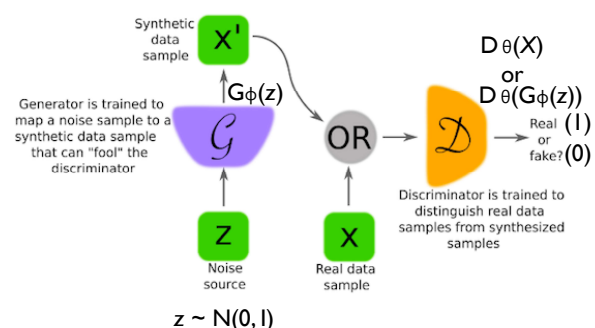
or

$$\text{minimize } (1 - \log D_\theta(G_\phi(z)))$$

Note:

[1] This is the objective function for just one sample z .

[2] Generator is a deterministic function i.e. for a sample z , it always gives the same result.



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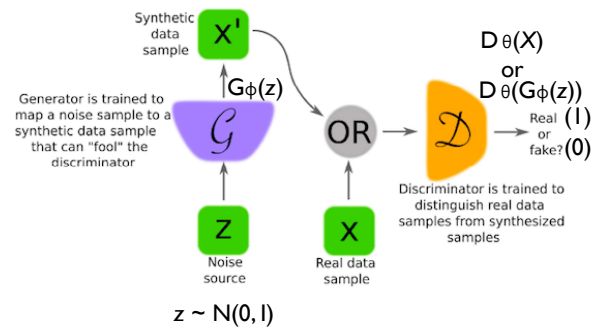
Mathematics of GANs

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- Since z is continuous and normal, the objective function for all the samples taken together would be:

$$\underset{\phi}{\text{minimize}} \int p(z) (1 - \log D_{\theta}(G_{\phi}(z)))$$



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- Discriminator's loss function has two components since Discriminator's task is two-fold (it should assign highest score to the real samples and the lowest score to the fake samples).

$$\underset{\theta}{\text{maximize}} \int p(x) \log D_{\theta}(x) + \int p(z) [\log (1 - D_{\theta}(G_{\phi}(z)))]$$

- The overall objective function comes out to be:

$$\underset{\phi}{\text{minimize}} \underset{\theta}{\text{maximize}} [\int p(x) \log D_{\theta}(x) + \int p(z) [\log (1 - D_{\theta}(G_{\phi}(z)))]]$$

Note: The Discriminator wants to maximize the second term and the Generator wants to minimize the second term.

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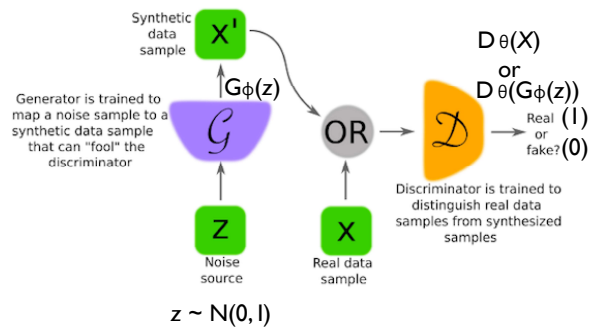
Main Steps Involved in Training GANs

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The training happens in two steps:

- **Step 1:** Perform Gradient Ascent (maximize the likelihood function) on the Discriminator.
- **Step 2:** Perform Gradient Descent (minimize the likelihood function) on Generator.



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Algorithm for Training GANs

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Algorithm 1 Minibatch stochastic gradient descent training of generative adversarial nets. The number of steps to apply to the discriminator, k , is a hyperparameter. We used $k = 1$, the least expensive option, in our experiments.

for number of training iterations **do**

for k steps **do**

- Sample minibatch of m noise samples $\{z^{(1)}, \dots, z^{(m)}\}$ from noise prior $p_g(z)$.
- Sample minibatch of m examples $\{x^{(1)}, \dots, x^{(m)}\}$ from data generating distribution $p_{\text{data}}(x)$.
- Update the discriminator by ascending its stochastic gradient:

$$\nabla_{\theta_d} \frac{1}{m} \sum_{i=1}^m [\log D(x^{(i)}) + \log (1 - D(G(z^{(i)})))]$$

end for

- Sample minibatch of m noise samples $\{z^{(1)}, \dots, z^{(m)}\}$ from noise prior $p_g(z)$.
- Update the generator by descending its stochastic gradient:

$$\nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^m \log (1 - D(G(z^{(i)})))$$

end for

Source: <https://papers.nips.cc/paper/5423-generative-adversarial-nets>

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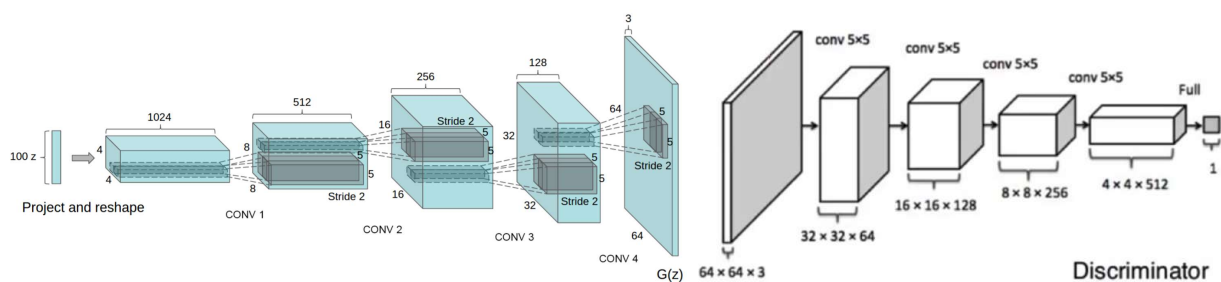
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Architecture of DCGAN

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Source: <https://arxiv.org/pdf/1511.06434.pdf>

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Time for a Quick Hands-on

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- Let's build our DCGAN (Deep Convolutional Generative Adversarial Network).
- This GAN will try to generate digits like found in MNIST dataset.
- Code available at:
https://github.com/greatdevaks/PyCon_Thailand_2019_GANs_Anmol_Krishan_Sachdeva

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Best Practices for DCGAN

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- 🔧 Replace the pooling layers with strided convolutions in the Discriminator and fractional-strided/transpose convolutions in the Generator.
- 🔧 Use Batch Normalization in both the Discriminator and the Generator.
- 🔧 Remove Fully Connected hidden layers from deeper architectures.
- 🔧 Use ReLU activation in the Generator for all the layers except for the output, which uses tanh activation.
- 🔧 Use Leaky ReLU activation in the Discriminator for all the layers.

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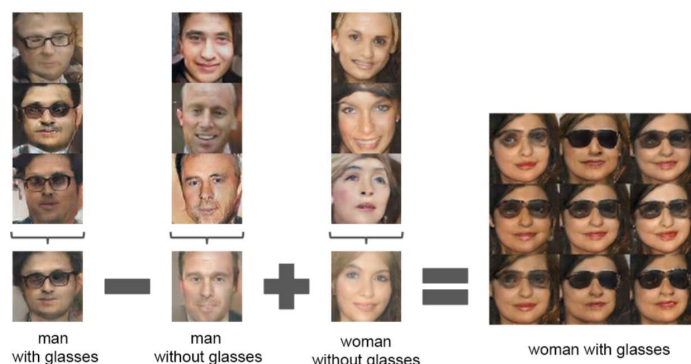
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Applications of GANs

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~ Vector Operations on Visual Objects:



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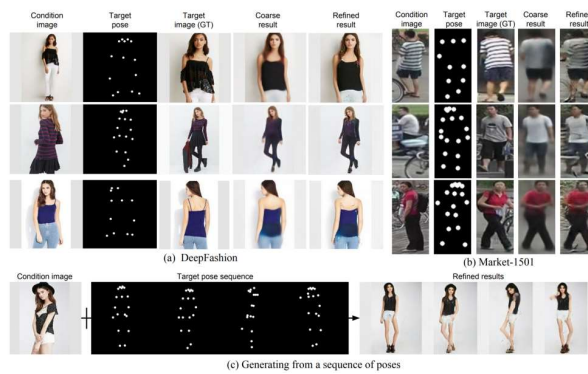
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~ Pose Guided Image Generation:



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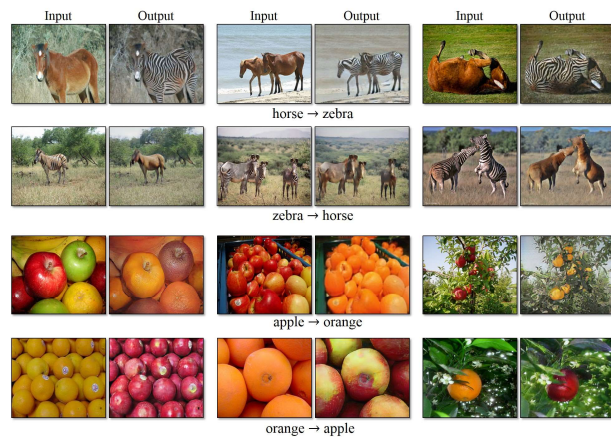
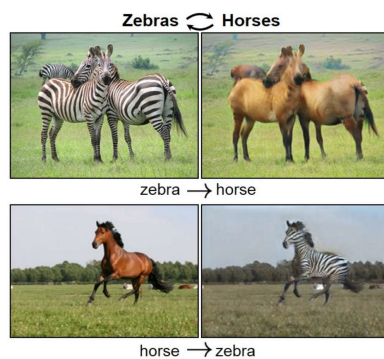
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~ CycleGAN [Link]:



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~ Progressive GAN - First Commercial-like Image Quality [\[Link to Paper\]](#):



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~ Test-to-Image using Stack GAN [\[Link\]](#):



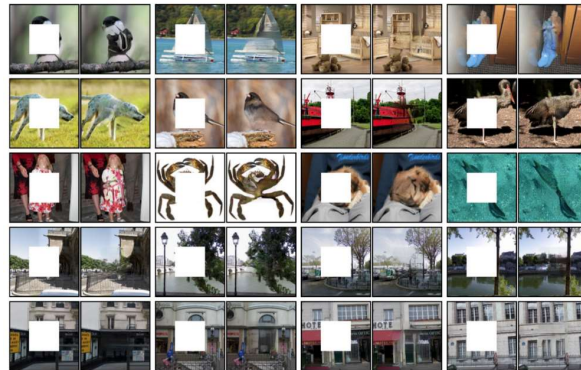
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THAILAND~ Image Inpainting using Context Encoder [\[Link\]](#):

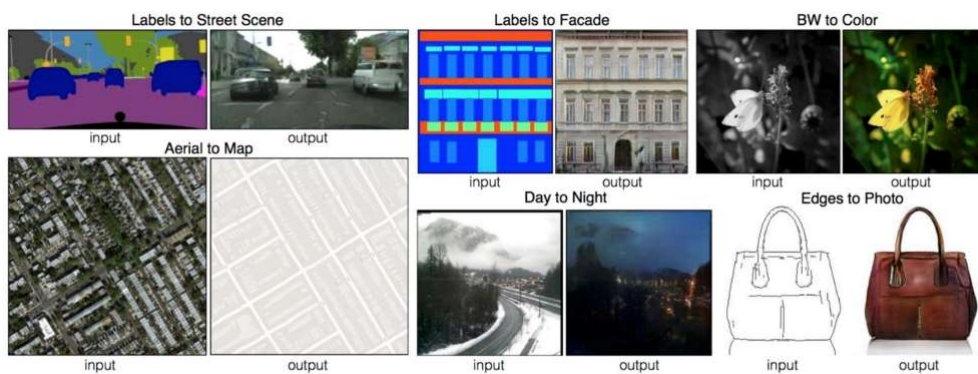
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THAILAND~ Image-to-Image Translation using Pix2Pix [\[Link\]](#):

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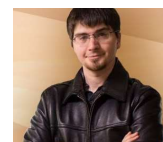
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Acknowledgements

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- 🌐 I thank PyCon Thailand's organizers and all the team members for making this happen.
- 🌐 I would like to thank Dr. Ian Goodfellow and all the researchers who have contributed towards the concept of GANs.
- 🌐 My sincere thanks to Prof. Cian O'Donnell, University of Bristol, UK and Prof. Carl Henrik Ek, University of Bristol, UK for imparting invaluable knowledge to me in this domain.
- 🌐 I would like to thank Bigbasket, India and all my team members for supporting and motivating me.



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Catch Me Next At...

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- 🌐 Speaking at GeoPython, Basel, Switzerland [June 25 – 27, 2019].
- 🌐 Speaking at EuroPython, Switzerland [July 8 – 14, 2019].

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Thanks a lot for being
such a nice audience

I WILL BE HAPPY TO ANSWER YOUR QUESTIONS...



Anmol Krishan Sachdeva

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GitHub: <https://www.github.com/greatdevaks>



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Time For Feedback

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🔗 It will take only 2 minutes. I will be highly obliged if you fill the feedback form.

🔗 Link: <https://greatdevaks.typeform.com/to/l9ycWM>

🔗 Note: No personal details asked.

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