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Cross -Domain Relations using Disco-GAN: Combining Lifestyle And Fashion

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ABSTRACT

While human beings are able to recognize relations between any 2 different domains without any supervision, learning automatically to discover relation is challenging and will require many ground truth pair to explain the relation.To avoid such situation which will require tremendous labels for pairing and will increase the complexity , we will discover cross domain relation between any two different domain with unpaired data.Here a cross domain model i.e. Deep Convolutional Generative Adversarial Network (DCGAN) is used which will generate a image which is present in other domain keeping the basic orientation and key attribues like face identity unchanged.This is also called Image to Image Translation technique. Relations between any two enties, objects present in different domains the way in which they are connected is ubiquitous.Here we propose a method which our model will learn and discover the relations between any two different domains.

Generative Adversarial Networks (GANS) are a new and advanced form of neural networks that have brought machines one step closer to humans by predicting features in a much better way due to adversarial training.Humans being the core target of matter for replication need to deal with tough decisions of what matching /contrasting apparels and accessories they want to wear on day to day basis .Fashion and lifestyle being the core areas of human lives still require time to think and decide upon.The networks in this technique will generate image of apparel/ accessory such as shoes etc on the basis of an input image of another apparel/accessory like purse keeping the pattern/style constant.This allows users to input any kind of apparel image and get the image of another matching apparel generated. It simplifies and provides a better variety to humans while creating a customized overall personality of themselves

Keywords— Generator , Discriminator, .Deep Convolutional Neural Networks, Reconstruction Loss, GAN LOSS.

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I. INTRODUCTION

Human beings can naturally recognize relations between any two domain. For instance consider English sentence translated in French and the translation and relationship the way in which it is translated is easily understood by humans naturally. Similarly we are training machine to learn the cross domain relation using DCGAN. Nowadays mostly all training approaches uses explicitly labeled data set. Explicit Supervised data is not often available and labeling can be tedious. Moreover pairing of images between 2 domain is uncertain if the image is missing in other domain or it may have multiple best images in other domain. There our other machine learning techniques and algorithms through which Mapping can happen but the labels are given explicitly or by humans. This is easy for small dataset but as the dataset increases it becomes tedious. DISCO GAN is based on unsupervised learning. Our model self discovers relations between them. With this primary notion of GANs with Fashion and lifestyle, a cross domain model is used which will generate images of one style to another image .It is also called as an Image-To-Image Translation technique. The networks in this technique will generate image of apparel/

accessory such as shoes etc on the basis of an input image of another apparel/accessory keeping the basic orientation constant. This allows users to input any kind of apparel image and get the image of another matching apparel generated. It simplifies and provides a better variety to humans while creating a customized overall personality of themselves. With the upcoming of new types of GANs the scope of application has widened to a great extent.

II. Literature Survey

1: Title: Batch Normalization: Accelerating Deep Network Training b y Reducing Internal Covariate Shift In this paper we have studied to train deep neural network using batch normalization.Batch normalization.When applied to image classification model the steps are reduced by 14 times. Authors:Sergey Ioffe, Christian Szegedy

2: Title: Generative Visual Manipulation on the Natural Image. In this paper we have studied to manipulate the image using GAN. Authors:Jun-Yan Zhu, P.hilipp Krahenbuhl

3: Title: To understand complex machine learning generative models using Interactive Visual Experiment. In this paper we have studied to implement GAN lab which helps to study GAN models. Author: Minsuk Kahng,Nikhil Thorat, Duen Horng Polo Chau, Georgia Fernanda B. Viegas, Martin Wattenberg.

4: Title: Conversion of text to realistic image using Stack GAN In this paper we studied that 2 stage stack GAN is used for implementing text to image conversion. Authors: Han Zhang1
Tao Xu2 Hongsheng Li3 Shaoting Zhang4 Xiaogang Wang3 Xiaolei Huang2 Dimitris Metaxas1

5: Title: Tutorial to Study Generative Adversial Network In this paper we studied basics of GAN and what is generative modeling. Authors: Ian Goodfellow

Sr. No.	Research Authors	Problem Studied
1.	Aubry, M., Maturana, D., Efros, A. A., Russell, B., and Sivic, J.	Computer Vision and Pattern Recognition .
2.	Isola, P., Zhu, J., Zhou, T., and Efros, A. A.	Image-to-image translation with conditional adversarial networks.
3.	Liu, M. and Tuzel, O.	Coupled generative adversarial networks
4.	Taigman, Y., Polyak, A., and Wolf, L	Unsupervised cross-domain image translation.
5.	Radford, A., Metz, L., and Chintala, S	Unsupervised representation learning with deep convolutional generative adversarial networks
6.	Mirza, M. and Osindero, S.	Conditional generative adversarial nets.

III. Architecture

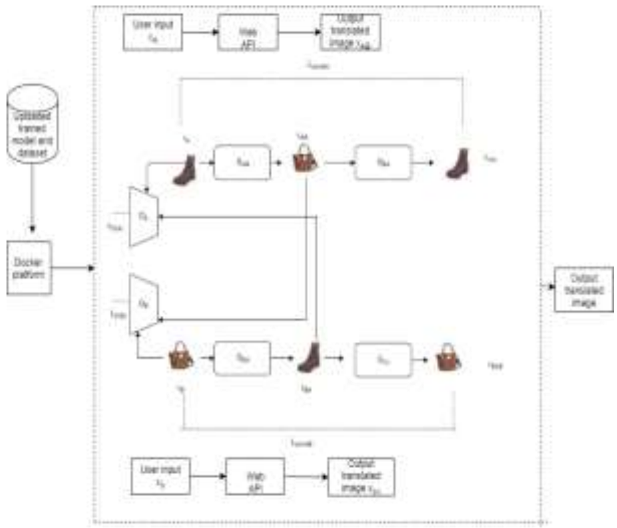


Fig 1 System Architecture

IV. Algorithms Used

1. **Discriminator Algorithm**

Step 1: For number of training iterators do(epochs).
Step 2: For k steps do(layers)
Step 3: Sample mini batch of m noise samples {z1…zm} from noise prior p{g(z)}
Step 4: Sample mini batch of m examples x...xm from data generation distribution.
Step 5: Update the discriminator by ascending its stochastic gradient.

$$\nabla \theta d = 1/m \sum [WgD(x1)+\log(1-D(G(z)))]$$

2. **Generator Algorithm**

- **Step I**: Sample mini batch of m noise samples z1.......zm from noise prior p(g(z))
- **Step II**: Update the generator by descending its stochastic gradient.

$$\nabla \theta g = 1/m \sum [Wg\log(1-D(G(z)))]$$

V. Working

1. Data Flow Diagram:

A data flow diagram (DFD) is a graphical illustration of the flow of data through an information system, modelling its process aspects. It shows data is processed by a system in terms of inputs and outputs.

For every data flow, at least one of the endpoints (source and or destination) must exist in a process. The refined representation of a process can be done in another data-flow diagram, which further divides this process into sub-processes.

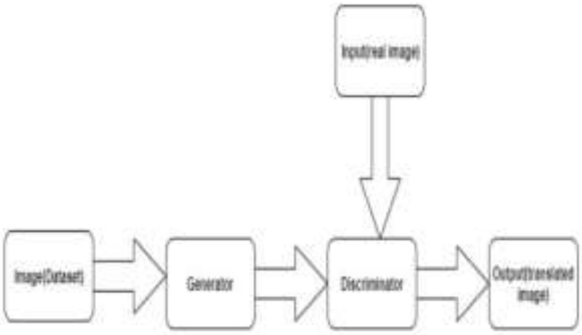


Fig 2 Data Flow of Image Translation

2. Deployment Diagram:

Deployment diagrams are used to picture the topology of the physical components of a system where the software components are deployed. The deployment diagram for the proposed system shows below. It shows the physical or the hardware components on which the software components. The physical components include the Server, Client, Windows JVM, and the Database.

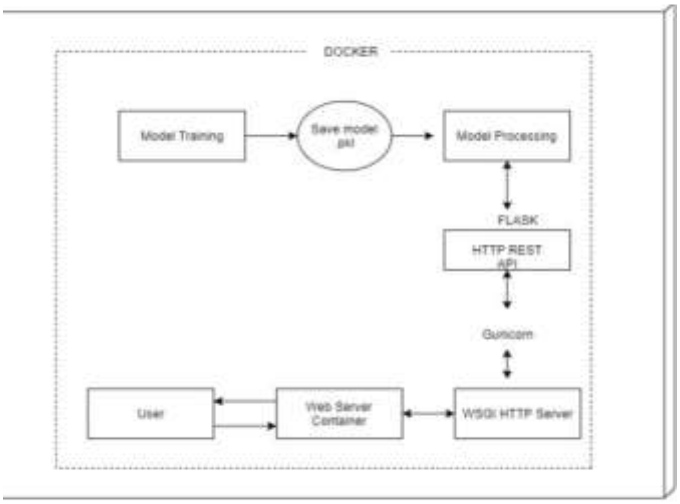
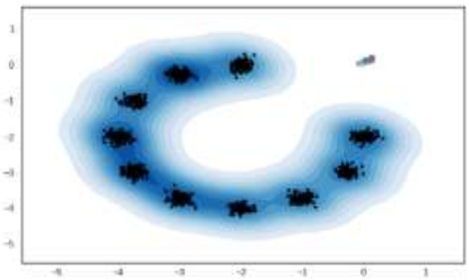
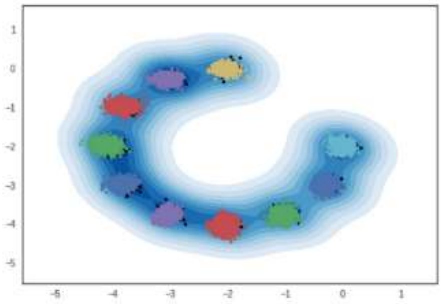


Fig 3 Deployment Diagram

VI. RESULTS



Iteration 0



Iteration 10000

VII. CONCLUSION

In this project we have implemented image translation between different domains using Disco GAN. We have acheived this with not providing explicit labels and generating the high resolution image. We can also implement edge to image or object translation e.g. car to shoe etc depending on domain.

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