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IMAGE REGENERATION WITH GENERATIVE MODELS

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ABHIJITH C.	**1MV14CS004**
RAGHAVA G. DHANYA	**1MV14CS077**
SHASHANK S.	**1MV14CS131**

Project carried out at
Sir M. Visvesvaraya Institute of Technology
Bangalore-562157

Under the Guidance of
MRS. SUSHILA SHIDNAL
Assistant Professor, Department of CSE
Sir M Visvesvaraya Institute of Technology, Bangalore.

Department Of Computer Science & Engineering
Sir M. Visvesvaraya Institute Of Technology
Hunasamaranahalli, Bangalore-56215

ABSTRACT

Current advances in Generative Adversarial Networks allow us to obtain near realistic images of faces but it is still quite distinguishable from actual photographic images. The technology is also not very amiable to changes in the orientation of faces in Convolutional Neural Networks(CNN). Additionally, the amount of data required to train the network must be exhaustible, for example, in case different perspectives of a face are required the various perspectives must be explicitly present in the training data to achieve the result. Thus the network requires humongous amounts of data.

In this paper we propose a novel approach to accomplish the same results using CapsNet. CapsNet employs a dynamic routing algorithm which replaces the scalar-output feature detectors of the CNN with vector-output capsules. A capsule is essentially a group of neurons describing a specific part of object or image. Active capsules at one level make predictions, via transformation matrices, for the instantiation parameters of higher-level capsules. In essence, the CapsNet is the reverse of the common Computer Graphics pipeline where we convert objects to their renders. The CapsNet works from the pixel level and works up towards the object.

We propose that the amount of data required to train a comparable model is very small while it gives comparable, if not better, results.

CONTENTS

INTRODUCTION

"What I cannot create, I do not understand."

Richard Feynman

One of the main aspirations of Artificial Intelligence is to develop algorithms and techniques that enrich computers with ability to understand our world. Generative models are one of the most promising approaches towards achieving this goal.

A generative model is a mathematical or statistical model to generate all values of a phenomena. To train such a model, we first collect a large amount of data in some domain (e.g., think millions of images, sentences, or sounds, etc.) and then train a model to generate data like it.

A generative algorithm models how data was generated to classify a signal. It poses the question: according to my generation hypotheses, which category is most likely to generate this signal? A discriminative algorithm does not care about how the data was generated, it just classifies a given signal. A generative model learns the joint probability distribution $p(x, y)$ while a discriminative model learns the conditional probability distribution $p(y|x)$ "probability of y given x".

The trick is that the neural networks that we use as generating models have a significantly smaller number of parameters than the amount of data on which we train them, so the models are forced to effectively discover and internalize the essence of the data to generate it.

There are multiple approaches to build a generative models

- Generative adversarial networks (GANs) are a class of generative algorithms used in unsupervised machine learning, implemented by a system of two neural networks competing in a zero-sum game framework. They were presented by Ian Goodfellow et al.[3]. This technique can generate photographs that seem at least superficially authentic to human observers, having many realistic features (though in tests people can tell real from generated in many cases).

- Variational Autoencoders (VAEs) allow us to formalize this problem in the framework of probabilistic graphical models where we are maximizing a lower bound on the log likelihood of the data

- Autoregressive models such as PixelRNN, on the other hand train a network that models the conditional distribution of every individual pixel given previous pixels (to the left and to the top). This is similar to plugging the pixels of the image into a char-rnn, but the RNNs runs both horizontally and vertically over the image instead of just a 1D sequence of characters.

Generative Adversarial Networks, which we already discussed above, pose the training process as a game between two distinct networks: a generator network (as seen above) and a second discriminative network that tries to classify samples as either coming from the true distribution $p(x)$ or the model distribution $\hat{p}(x)$. Every time the discriminator notices a difference between the two distributions the generator adjusts its parameters slightly to make it go away, until at the end (in theory) the generator exactly reproduces the true data distribution and the discriminator is guessing at random, unable to find a difference.

Literature Survey

"Adversarial training is the coolest thing since sliced bread"

Yann LeCun,
Director of AI Research at Facebook and Professor at NYU

GANs were first introduced by Ian Goodfellow *et al.* [3] in Neural Information Processing Systems 2014. The paper proposes a completely new framework for estimating generative models via an adversarial process. In this process two models are simultaneously trained. According to [3] the network has a generative model G that captures the data distribution, and a discriminative model D that estimates the probability that a sample came from the training data rather than G. This original work by Ian Goodfellow uses fully connected neural networks in the generator and the discriminator.

Since then, there has been tremendous advancements in Deep Learning. A convolutional neural network (CNN, or ConvNet) [6] is a class of deep, feed-forward artificial neural networks that has successfully been applied to analyzing visual imagery. The convolution layer parameters consist of a set of learn-able filters, also called as kernels, which have a small receptive field, but they extend through the full depth of the input volume. As a result, the network learns filters that activate when it detects some specific type of feature at some spatial position in the input.

A breakthrough development that occurred in Adversarial Networks was the introduction of "Deep Convolutional Generative Adversarial Networks" by Alec Radford *et al*[10]. He applied a list of empirically validated tricks as the substitution of pooling and fully connected layers with convolutional layers.

The power of the features encoded in the latent variables was further explored by Chen at al. [2]. They propose an algorithm which is completely unsupervised, unlike previous approaches which involved supervision, and learns interpretable and disentangled representations on challenging datasets. Their approach only adds a negligible computation cost on top of GAN and is easy to train.

Today, most GANs are loosely based on the former shown DCGAN [10] architecture. Many papers have focused on improving the setup to enhance stability and performance. Many key insights was given by Salimans *et al.*[12], like Usage of convolution with stride instead of pooling, Usage of Virtual Batch Normalization, Usage of Minibatch Discrimination in DD, Replacement of Stochastic Gradient Descent with Adam Optimizer [6], Usage of one-sided label smoothing.

Another huge development came with the introduction of Wasserstein GANs by Martin Arjovsky [1] . He introduced a new algorithm named WGAN, an alternative to traditional GAN training. In this new model, he showed that the stability of learning can be improved, remove problems like mode collapse, and provide good learning curves useful for debugging and hyperparameter searches.

This recently proposed Wasserstein GAN (WGAN) [1] makes progress toward stable training of GANs, but sometimes can still generate only low-quality images or fail to converge. Ishaan Gulrajani with Martin Arjovsky proposed an alternative in [4] to fix the issues the previous GAN faced. This proposed method performs better than standard WGAN and enables stable training of a wide variety of GAN architectures with almost no hyperparameter tuning, including 101-layer ResNets[5] and language models over discrete data.

Work by Mehdi Mirza *et al.*[8] introduced the conditional version of GAN which can be constructed by simply feeding the data, y, we wish to condition on to both the generator and discriminator. The CGAN results were comparable with some other networks, but were outperformed by several other approaches – including non-conditional adversarial nets.

Sebastian Nowozin *et al.*[9] discussed the benefits of various choices of divergence functions on training complexity and the quality of the obtained generative models. They show that any f-divergence can be used for training generative neural samplers.

Ming-Yu *et al.*[7] proposed coupled generative adversarial network (CoGAN) for learning a joint distribution of multi-domain images. The existing approaches requires tuples of corresponding images in different domains in the training data set. CoGAN can learn a joint distribution without any tuple of corresponding images.

A big breakthrough in the field of Deep Learning came with the introduction of CapsNets or Capsule Networks[11] by the Godfather of Deep Learning, Geoffrey Hinton. CNNs perform exceptionally great when they are classifying images which are very close to the data set. If the images have rotation, tilt or any other different orientation then CNNs have poor performance. This problem was solved by adding different variations of the same image during training.

OBJECTIVE

"Any A.I. smart enough to pass a Turing test is smart enough to know to fail it."

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Ian McDonald,
River of Gods

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The broad objective is to use the existing Generative Adversarial Networks technologies to aid in the generation of human faces such that the GAN generated images is indistinguishable from the images of the real people used to train the network, i.e fake images should look very much real. This would be then extended to completion of faces, ie. reconstruction of facial features given a partial face.

The internal specific objective would be to achieve the above said objectives using a ground breaking technology released in fall 2017, the Capsule Nets. The existing latest state-of-the-art GAN architectures use Convolution Neural Networks in their Generators and Discriminators. The CNNs are said to have the drawbacks as mentioned before, where they cannot understand orientation and spatial relationships unless they are extensively trained with all possible images. This major drawback is handled by Capsule Networks.

Using the CapsNet architecture into the Generator/Discriminator could improve these Adversarial Networks quite drastically. This mating of the revolutionary Generative Adversarial Networks along with the ground-breaking Capsule Networks, resulting in "Capsule Net GANs" is the overarching objective.

SCOPE

"By far the greatest danger of Artificial Intelligence is that people conclude too early that they understand it."

Eliezer Yudkowsky,
Machine Intelligence Research Institute

Generative Adversarial Networks are one of the hottest topics in Deep Learning right now. The applications of GANs are far ranging and immense. Creating Info-graphics from text, creating animations for rapid development of marketing content, generating website designs are to name a few. Our focus in this project is to implement a way to complete images of faces by generating the missing pieces using a GAN.

This particular implementation of the technology would be immensely useful in a variety of circumstances. A few straightforward applications include face sketching of suspects in a crime using eye witness accounts, super resolution of CCTV camera footage to enhance faces, filling in of old degraded color photos, etc.

METHODOLOGY

> *"Artificial intelligence, in fact, is obviously an intelligence transmitted by conscious subjects, an intelligence placed in equipment."*

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Pope Benedict XVI

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The first step would be to implement the state-of-the-art in image regeneration to guage the improvements. We use DCGAN to start of with. The results of the training and testing will be recorded to compare it with the results of our CapsNet-based approach later. We will be using CapsNet as the underlying technology to implement our GAN (CapsGAN). The goal is to replace the CNN inside DCGAN with CapsNet and compare the results. The GAN internally consists of two components - a generator and a discriminator - which we build out of CapsNet. The discriminator is initially trained separately to distinguish real and fake data, and later they work together to improve upon their performance by acting as adversaries.
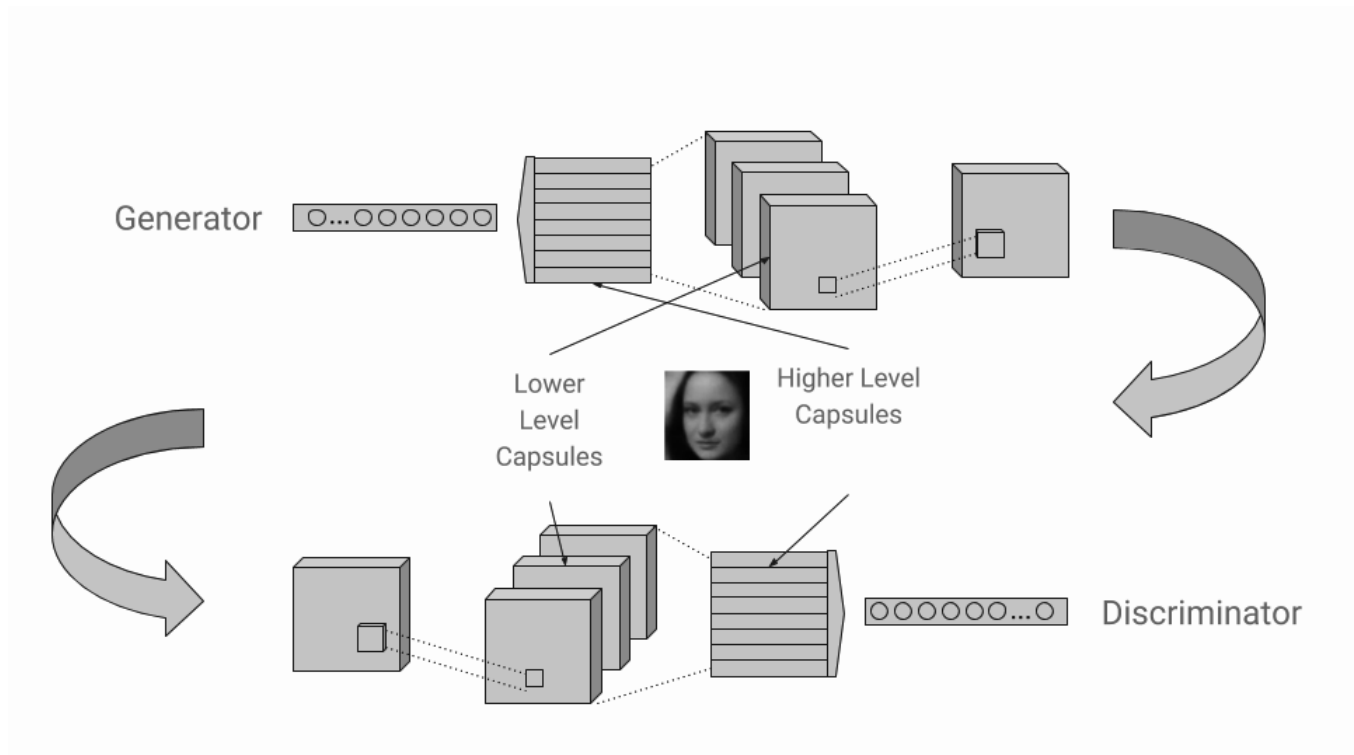

Figure 5.1: Proposed architecture

The generator will use noise as input to generate faces. We will use random data as this noise. This ensures the data is unique and across the spectrum while retaining a normal distribution.

The CapsNet making up the discriminator consists of a small convolutional network to convert low level data in the form of pixels into an artifact called "pose". These poses can be anything, like nose, ear,

eye, etc. These poses are then passed on as input to the later lower layers consisting of components called Capsules. A capsule is analogous to the human brain containing different modules to handle different tasks. The brain has a mechanism to route the information among the modules, to reach the best modules that can handle the information.

A capsule is a nested set of neural layers. Each capsule is able to handle one particular pose and communicate its calculation to other capsules which can use that calculation. This calculation is in the form of a probability prediction of the current pose that takes place in its logistic unit. This working is fundamentally different from convolutional networks, which utilizes Max Pooling. Max pooling selects the most active input node from the next layer to pass on the information. CapsNet on the other hand selects the next capsule based on which capsule would be capable of handling that information. This is called Dynamic routing. This results in invariance of information to the position and orientation of features in an object while ignoring the invariance in very low level features as, at the pixel level, this does not matter.

The generator is built using an architecture that is a mirror image of the discriminator. Inside, the data flow is in the opposite direction. The job of the discriminator is to take the images given out by the generator and discriminate it against a ground truth. The discriminator selects the class based on how close the images are in agreement. The underlying principle is that when multiple entities agree with each other in higher dimensions, the chances of it happening due to complete coincidence is exponentially minimal. This ensures the understanding by the CapsNet of the world is remarkably similar to humans.

TECHNOLOGY

"I think, therefore I am"

René Descartes,
French philosopher and scientist

- **Adversarial Training:** Two models undergoing training simultaneously by competing against each other. The output of each model acts as an adversary for the other to improve upon.

- **Generative Model:** Any model capable of generating completely new realistic data of a class.

- **Discriminative Model:** Here, as a Discriminator, a model which is capable of distinguishing between actual ground truth from the true distribution and generated information from a model.

- **Gradient Descent:** A method of optimizing an objective function using a first-order iterative approach to find a local minimum.

- **Gaussian Model:** A model that fits the data in the shape of a Gaussian function, identified by a characteristic "bell curve". CapsNet uses this to find agreeing probability outputs of the "capsules".

- **TensorFlow:** An open source software library for numerical computation using data flow graphs. It was originally developed by the Google Brain Team within Google's Machine Intelligence research organization for machine learning and deep neural networks research.

Other essentials:

- **CPU:** 3GHz quad core, x86-64 architecture (or)

- **GPU:** NVIDIA or any other TensorFlow supported GPU, CUDA or cuDNN

- **Python:** 2.7 or 3.4 and above

CONCLUSION

"A year spent in artificial intelligence is enough to make one believe in God"

Alan Perlis,
First Turning award recipient

During the course of this project, we wish to replicate the results of the existing state-of-the-art in Generative Models. Using this as a stepping stone, we would like to incorporate a hitherto unexplored option in CapsNet for Generative Models. Our motivating assumption is that CapsNet would provide a performance improvement.We base this on the idea that it is more capable of understanding the variances in objects. This in turn should lead to lower data requirements during training of the model and consequently lower power consumption.

We wish to provide a comparison between our novel CapsNet-based approach and other implementations of GAN for the same task. We would like to implement a proof of concept by developing a application to complete incomplete images of human faces. This could later on be used in enhancement of hazy CCTV footage to identify individuals, which would be immensely helpful to law enforcement personnel.

Head of Department

Project Guide   **Project Coordinator**

REFERENCES

[1] Martin Arjovsky, Soumith Chintala, and Léon Bottou. Wasserstein generative adversarial networks. In Doina Precup and Yee Whye Teh, editors, *Proceedings of the 34th International Conference on Machine Learning*, volume 70 of *Proceedings of Machine Learning Research*, pages 214–223, International Convention Centre, Sydney, Australia, 06–11 Aug 2017. PMLR.

[2] Xi Chen, Xi Chen, Yan Duan, Rein Houthooft, John Schulman, Ilya Sutskever, and Pieter Abbeel. Infogan: Interpretable representation learning by information maximizing generative adversarial nets. In D. D. Lee, M. Sugiyama, U. V. Luxburg, I. Guyon, and R. Garnett, editors, *Advances in Neural Information Processing Systems 29*, pages 2172–2180. Curran Associates, Inc., 2016.

[3] Ian Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. Generative adversarial nets. In Z. Ghahramani, M. Welling, C. Cortes, N. D. Lawrence, and K. Q. Weinberger, editors, *Advances in Neural Information Processing Systems 27*, pages 2672–2680. Curran Associates, Inc., 2014.

[4] Ishaan Gulrajani, Faruk Ahmed, Martin Arjovsky, Vincent Dumoulin, and Aaron C Courville. Improved training of wasserstein gans. In I. Guyon, U. V. Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, and R. Garnett, editors, *Advances in Neural Information Processing Systems 30*, pages 5767–5777. Curran Associates, Inc., 2017.

[5] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. *CoRR*, abs/1512.03385, 2015.

[6] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. Imagenet classification with deep convolutional neural networks. In F. Pereira, C. J. C. Burges, L. Bottou, and K. Q. Weinberger, editors, *Advances in Neural Information Processing Systems 25*, pages 1097–1105. Curran Associates, Inc., 2012.

[7] Ming-Yu Liu and Oncel Tuzel. Coupled generative adversarial networks. In D. D. Lee, M. Sugiyama, U. V. Luxburg, I. Guyon, and R. Garnett, editors, *Advances in Neural Information Processing Systems 29*, pages 469–477. Curran Associates, Inc., 2016.

[8] Mehdi Mirza and Simon Osindero. Conditional generative adversarial nets. *CoRR*, abs/1411.1784, 2014.

[9] Sebastian Nowozin, Botond Cseke, and Ryota Tomioka. f-gan: Training generative neural samplers using variational divergence minimization. In D. D. Lee, M. Sugiyama, U. V. Luxburg, I. Guyon, and R. Garnett, editors, *Advances in Neural Information Processing Systems 29*, pages 271–279. Curran Associates, Inc., 2016.

[10] Alec Radford, Luke Metz, and Soumith Chintala. Unsupervised representation learning with deep convolutional generative adversarial networks. *CoRR*, abs/1511.06434, 2015.

[11] Sara Sabour, Nicholas Frosst, and Geoffrey E Hinton. Dynamic routing between capsules. In I. Guyon, U. V. Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, and R. Garnett, editors, *Advances in Neural Information Processing Systems 30*, pages 3856–3866. Curran Associates, Inc., 2017.

[12] Tim Salimans, Ian Goodfellow, Wojciech Zaremba, Vicki Cheung, Alec Radford, Xi Chen, and Xi Chen. Improved techniques for training gans. In D. D. Lee, M. Sugiyama, U. V. Luxburg, I. Guyon, and R. Garnett, editors, *Advances in Neural Information Processing Systems 29*, pages 2234–2242. Curran Associates, Inc., 2016.