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Class: DATS 6303 - 10 Deep Learning

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Final Project Proposal - Group 7

### **Topic**

Generating Photorealistic Images of Dogs using Generative Adversarial Networks (GANs)

Our project will focus on generating photorealistic images of dogs using Generative Adversarial Networks (GANs). The choice of this problem is driven by the complexity and diversity of dog features, which poses an exciting challenge in synthetic image generation. Successful implementation can significantly contribute to advancements in Al-generated art and data augmentation techniques for machine learning models.

#### **Dataset**

For this project, we will use the Stanford Dogs dataset. This dataset has 20,580 images across 120 breeds, providing a diverse and extensive training set for a deep-learning model. It includes annotations such as class labels and bounding boxes, which can be leveraged to enhance the training process.

# **Network Type**: GAN (Generative Adversarial Networks)

GAN architecture consists of two primary components: The Generator and the Discriminator (Aggarwal, A, 2021). Both of these are neural networks, where the role of the Generator is to learn how to create more plausible images. At the same time, the Discriminator attempts to evaluate both authentic images (as positive) and the images generated by the generator (as negative). As they compete, the Generator becomes better and better at creating fake images, until they become more challenging to distinguish from the real images for the Discriminator. The discriminator's classification signals the generator to update its weights in backpropagation (Google, 2022).

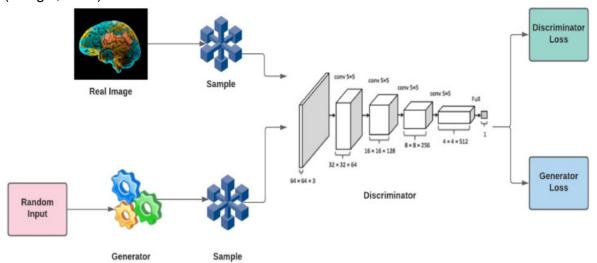


Figure 1: GAN architecture

Customization: To achieve better results, we will experiment with the GAN architecture, like adjusting the number of layers or the number of filters in convolutional layers to optimize the image quality. Additionally, other techniques like batch normalization, dropout, or different activation functions can also be applied to stabilize the training process and improve the quality of generated images. There are also many versions of GAN, like conditional GAN (cGAN), and Instance-Conditioned GAN (IC-GAN), that we may reference throughout our project. Framework: PyTorch Tensorflow

### References

- Aggarwal, A., Mittal, M., Battineni, G., & times, A. recent. (2021, January 28). *Generative Adversarial Network: An overview of theory and applications*. International Journal of Information Management Data Insights.
  - https://www.sciencedirect.com/science/article/pii/S2667096820300045
- Google. (2022, July 18). *Introduction* | *machine learning* | *google for developers*. Google. https://developers.google.com/machine-learning/gan/

### **Loss Function References**

- Goodfellow, I. J., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., ...
  Bengio, Y. (2014). Generative Adversarial Networks. arXiv [Stat.ML]. Retrieved from http://arxiv.org/abs/1406.2661
- Arjovsky, M., Chintala, S., & Bottou, L. (2017). Wasserstein GAN. arXiv [Stat.ML]. Retrieved from http://arxiv.org/abs/1701.07875

# **Performance Index**

Because the GAN architecture is essentially two competing neural networks, we will need loss functions that can be maximized by the discriminator and minimized by the generator. Two standard loss functions for the two distributions in GAN are minimax loss, and Wasserstein loss, described in <a href="https://arxiv.org/abs/1406.2661">https://arxiv.org/abs/1406.2661</a> (Goodfellow, 2014), and <a href="https://arxiv.org/abs/1701.07875">https://arxiv.org/abs/1701.07875</a> (Arjovsky, 2017), respectively. Generally, the parts of the loss function are the critic's output for real and fake instances (can be a probability), and the generator's production given the noise for image generation. We will also look into more loss functions available in PyTorch and TensorFlow.

# <Time Schedule>

- Week 1 (~ Nov 4): Final Project Proposal / Literature Review
- Week 2 (~ Nov 11): Literature Review / Data Loading, EDA, Data Preprocessing
- Week 3 (~ Nov 18): Model Training
- Week 4 (~ Nov 25): Model Evaluation (Fall Break)
- Week 5 (~ Dec 2): Preparation for Presentation and Submission
- Week 6 (~ Dec 5): Preparation for Presentation and Submission

Github repo: https://github.com/eitanaka/DL\_Final\_Project\_Group7