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Graph Theory Major Assignment

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Introduction To Deep Generative Modeling

Research Paper Summary

# 1. Introduction

Deep Generative Models (DGMs) are advanced neural networks designed to approximate complex, high-dimensional probability distributions. These models have wide-ranging applications, including generating realistic images, sounds, and videos. Despite their successes, challenges persist, particularly in training and designing effective models. This paper offers a concise mathematical framework for three prominent DGM approaches: Normalizing Flows (NF), Variational Autoencoders (VAEs), and Generative Adversarial Networks (GANs). The authors emphasize their similarities with optimal transport theory to encourage further research.

# 2. Literature Review

The authors provide an overview of the field’s rapid development, highlighting the strengths and limitations of existing methods:

* Normalizing Flows (NF): Effective for invertible transformations but restricted when data and latent dimensions differ.
* Variational Autoencoders (VAEs): Overcome invertibility issues but require an approximate posterior distribution for training.
* Generative Adversarial Networks (GANs): Address distribution comparisons without needing latent variables but face training instability. Additionally, the paper links DGMs to optimal transport methods, showing potential for theoretical advancements.

# 3. Methodology

The study outlines three key DGM methods:

* Normalizing Flows (NFs): Model invertible transformations between data and latent distributions. Training optimizes likelihood estimates via maximum likelihood and involves designing reversible, differentiable layers.
* Variational Autoencoders (VAEs): Introduce an approximate posterior for non-invertible models. The Evidence Lower Bound (ELBO) is optimized to balance reconstruction quality and regularity of latent variables.
* Generative Adversarial Networks (GANs): Use a discriminator network to differentiate real and generated samples, training the generator adversarially. Each method was evaluated on toy problems, such as the "two moons" dataset and high-dimensional MNIST data, to illustrate their practical performance.

# 4. Results

Normalizing Flows: Provided smooth transformations and reliable density estimates but struggled with high-dimensional data when assumptions were not met.

* VAEs: Performed well for MNIST data, producing meaningful latent representations and quality reconstructions. However, balancing reconstruction and latent space regularity remained challenging.
* GANs: Successfully generated realistic images but were sensitive to model and training choices, requiring fine-tuning to stabilize adversarial dynamics.

## 5. Discussion

The authors discuss trade-offs between expressiveness, training feasibility, and interpretability for each approach:

* NF models work best when data dimensionality aligns with latent space but require efficient invertibility.
* VAEs offer flexibility but introduce a trade-off between latent structure and reconstruction fidelity.
* GANs excel at generating high-quality samples but often lack guarantees for statistical alignment with the target distribution. The connection to optimal transport highlights potential avenues for improving model robustness and interpretability.

# 6. Conclusion

The paper underscores the promise and challenges of DGMs. While each approach has unique advantages, their application depends on data characteristics and computational constraints. Future research should focus on hybrid models, integrating ideas across methodologies to address current limitations.