

Enhancing capabilities of generative models through VAE-GAN integration: A review

Dongting Cai

Macau University of Science and Technology, China

1220004466@student.must.edu.mo

Abstract. Our review explores the integration of Variational Autoencoders (VAEs) and Generative Adversarial Networks (GANs), which are pivotal in the realm of generative models. VAEs are renowned for their robust probabilistic foundations and capacity for complex data representation learning, while GANs are celebrated for generating high-fidelity images. Despite their strengths, both models have limitations: VAEs often produce less sharp outputs, and GANs face challenges with training stability. The hybrid VAE-GAN models harness the strengths of both architectures to overcome these limitations, enhancing output quality and diversity. We provide a comprehensive overview of VAEs and GANs technology developments, their integration strategies, and resultant performance improvements. Applications across various fields, such as artistic creation, medical imaging, e-commerce, and video gaming, highlight the transformative potential of these models. However, challenges in model robustness, ethical concerns, and computational demands persist, posing significant hurdles. Future research directions are poised to transform the VAE-GAN landscape significantly. Enhancing training stability remains a priority, with new approaches such as incorporating self-correcting mechanisms into GANs training being tested. Addressing ethical issues is also critical, as policymakers and technologists work together to develop standards that prevent misuse. Moreover, reducing computational costs is fundamental to democratizing access to these technologies. Projects such as the development of MobileNetV2 have made strides in creating more efficient neural network architectures that maintain performance while being less resource-intensive. Further, the exploration of VAE-GAN applications in fields like augmented reality and personalized medicine offers exciting opportunities for growth, as evidenced by recent pilot studies.

Keywords: VAEs, GANs, VAE-GAN, Generative Models, Machine Learning

1. Introduction

The domain of machine learning is marked by rapid evolution, with generative models spearheading numerous groundbreaking advancements [1]. Variational Autoencoders (VAEs) and Generative Adversarial Networks (GANs) are prominent among these models, which have brought about revolutionary changes in data generation and representation learning [2]. VAEs, developed by Kingma and Welling, are lauded for their robust probabilistic frameworks and efficient latent representation learning capabilities, offering substantial benefits across a broad spectrum of machine learning applications [3]. Meanwhile, GANs, introduced by Goodfellow et al., have set new standards in the

field with their ability to generate exceptionally realistic and detailed images, fundamentally transforming image synthesis [1].

Despite their successes, both models exhibit inherent limitations that affect their functionality and broader applicability [4]. VAEs are robust but often yield outputs that lack the desired sharpness for high-quality image synthesis—a limitation that becomes particularly apparent in applications requiring fine detail [5]. On the other hand, GANs, while providing superior image quality, are notorious for their training challenges, including instability and mode collapse, where the generator fails to represent the diversity of input data adequately [4]. These challenges have spurred interest in hybrid models like VAE-GANs, which synergistically combine the generative prowess of GANs with the structured probabilistic approach of VAEs [4]. This integration aims to produce outputs that are not only high-quality but also diverse, effectively addressing the limitations posed by each model when operating separately.

Our review delves into the symbiotic integration of VAEs and GANs, exploring the synergies this combination harnesses [6]. We examine each model's developmental trajectories and integration strategies, evaluating the enhancements in performance and scope of application resulting from their union [7]. The transformative impacts of VAE-GANs are particularly notable across diverse domains, such as creative media, medical imaging, personalized commerce, and interactive entertainment, significantly pushing the boundaries of what can be achieved with generative models [8].

Furthermore, we address the ongoing challenges, such as computational efficiency and ethical concerns surrounding the deployment of these models [9]. These issues are critical as they influence the practical deployment and societal perception of VAE-GAN technologies [10]. In conclusion, we propose future research directions to refine VAE-GAN integrations and broaden their practical applications, ensuring that these innovative models continue to evolve within ethical bounds and contribute positively to technological progress.

2. Background

2.1. VAEs

Introduced by Kingma and Welling in 2013, VAEs have marked a significant advancement in generative models [11]. These models utilize a probabilistic graphical framework that enables them to learn latent representations in an unsupervised way, providing a robust approach to model training and a deeper understanding of underlying data distributions. The strength of VAEs lies in their ability to efficiently encode data into a latent space, where complex distributions are modeled with a network that learns to approximate the posterior probabilities [12]. This capability has been instrumental in improving the quality of generated outputs while ensuring that the model remains tractable and theoretically sound.

The loss function $\mathcal{L}(\theta, \phi; \mathbf{x}^{(i)})$ for VAEs, which guides the training process, is composed of two terms: the KL divergence $D_{KL}(q_{\phi}(\mathbf{z}|\mathbf{x}^{(i)})||p_{\theta}(\mathbf{z}))$ that regularizes the encoder by comparing the encoded distribution with a prior distribution, and the reconstruction loss $\mathbb{E}_{q_{\phi}(\mathbf{z}|\mathbf{x}^{(i)})}[\log p_{\theta}(\mathbf{x}^{(i)}|\mathbf{z})]$ that encourages the decoded samples to match the original inputs. This balance helps in learning meaningful latent spaces:

$$\mathcal{L}(\theta, \phi; \mathbf{x}^{(i)}) = -D_{KL}(q_{\phi}(\mathbf{z}|\mathbf{x}^{(i)})||p_{\theta}(\mathbf{z})) + \mathbb{E}_{q_{\phi}(\mathbf{z}|\mathbf{x}^{(i)})}[\log p_{\theta}(\mathbf{x}^{(i)}|\mathbf{z})], \quad (1)$$

where θ are the parameters of the generative model $p_{\theta}(\mathbf{x}^{(i)}|\mathbf{z})$, ϕ are the parameters of the variational approximation $q_{\phi}(\mathbf{z}|\mathbf{x}^{(i)})$, \mathbf{x} represents the observed data, and \mathbf{z} represents the latent variables.

2.2. GANs

Developed by Goodfellow et al. in 2014, GANs have revolutionized the landscape of generative models with a novel architecture that pits two neural networks against each other: one to generate data

(the generator) and one to evaluate it (the discriminator) [13]. This game-theoretic approach initially facilitated the production of synthesized images, yet these early models often lacked the resolution and detail required for high fidelity. The original GANs were praised for their innovative approach to unsupervised learning, enabling machines to mimic complex data distributions. However, the images produced in these initial models, while intriguing, did not achieve the high-definition quality seen in subsequent developments.

Significant advancements were made through subsequent research that introduced several key modifications to the original GANs architecture. Deep Convolutional GANs (DCGAN), introduced by Radford et al., marked one of the first major improvements, employing convolutional neural networks to enhance the quality of generated images, leading to much clearer and higher definition results [14]. Following this, Wasserstein GANs (WGAN) addressed one of the main challenges in training GANs—training stability. The introduction of the Wasserstein loss function helped in stabilizing the learning process, allowing for more consistent production of high-quality images [15]. Additionally, Progressive GANs allowed the network to start with low-resolution images and progressively increase their resolution, which significantly enhanced the detail and quality of the output [16].

These enhancements have allowed GANs to produce images that are nearly indistinguishable from real photographs, which has been revolutionary in fields such as artistic creation, where they are used to generate novel artworks, and in medical imaging, where they assist in creating detailed medical scans for training and research purposes. The evolution of GANs continues to be a pivotal area of research in artificial intelligence, pushing the boundaries of creative and technical possibilities within various industries.

The objective function of GANs describes a minimax game where the discriminator aims to maximize its accuracy in distinguishing real data from fake, and the generator strives to fool the discriminator:

$$\min_G \max_D V(D, G) = \mathbb{E}_{\mathbf{x} \sim p_{\text{data}}(\mathbf{x})} [\log D(\mathbf{x})] + \mathbb{E}_{\mathbf{z} \sim p_z(\mathbf{z})} [\log (1 - D(G(\mathbf{z})))] \quad (2)$$

where G represents the generator network, D represents the discriminator network, \mathbf{x} are data samples drawn from the real data distribution $p_{\text{data}}(\mathbf{x})$, and \mathbf{z} are input noise samples drawn from a prior noise distribution $p_z(\mathbf{z})$.

2.3. Integration of VAEs and GANs

Integrating VAEs and GANs into cohesive VAE-GAN frameworks harnesses the encoding efficiency of VAEs with the generative capabilities of GANs to overcome some of the primary limitations faced by each model when used independently [17]. Larsen et al. proposed this hybrid approach in 2015, where the model uses a VAE's encoding strategies to feed into a GAN's generator, effectively improving the sharpness and diversity of the images produced while maintaining training stability [18]. This integration mitigates issues such as VAE's tendency to produce blurred images and GAN's susceptibility to mode collapse and enhances the overall robustness of generative tasks [8]. Subsequent adaptations, such as the introduction of Conditional VAEs and enhancements in loss functions, have continued to refine this approach, broadening the scope and applicability of VAE-GANs in more complex and varied domains [6]. To elucidate further on the technical workings of VAEs and GANs, consider their combined application in VAE-GANs, which leverages the VAE's encoding capabilities to structure a latent space that the GAN's generator then utilizes to produce refined outputs. This hybrid approach addresses the fundamental limitations of each model: the VAE's tendency to generate blurred images and the GAN's training instability due to mode collapse.

The VAE-GAN framework utilizes a combined loss function $\mathbb{E}_{q(\mathbf{z}|\mathbf{x})} [\log p(\mathbf{x}|\mathbf{z})]$ that incorporates the VAE's reconstruction and regularization losses $D_{\text{KL}}(q(\mathbf{z}|\mathbf{x})||p(\mathbf{z}))$ with the GAN's adversarial loss $[\log (\text{Dis}(\mathbf{x})) + \log (1 - \text{Dis}(\text{Gen}(\mathbf{z})))]$, aiming to optimize both the generation of realistic images and the meaningful encoding of data:

$$\mathcal{L}_{\text{like}}^{\text{pixel}} = -\mathbb{E}_{q(\mathbf{z}|\mathbf{x})}[\log p(\mathbf{x}|\mathbf{z})], \quad (3)$$

$$\mathcal{L}_{\text{prior}} = D_{\text{KL}}(q(\mathbf{z}|\mathbf{x})||p(\mathbf{z})), \quad (4)$$

$$\mathcal{L}_{\text{GAN}} = \log(\text{Dis}(\mathbf{x})) + \log(1 - \text{Dis}(\text{Gen}(\mathbf{z}))), \quad (5)$$

$$\mathcal{L}_{\text{VAE-GAN}} = \mathcal{L}_{\text{prior}} + \mathcal{L}_{\text{like}}^{\text{Dis}_l} + \mathcal{L}_{\text{GAN}}, \quad (6)$$

where $\mathcal{L}_{\text{like}}^{\text{Dis}_l}$ replaces $\mathcal{L}_{\text{like}}^{\text{pixel}}$ with a feature-wise metric.

3. Applications

The integration of VAEs and GANs has catalyzed significant advancements in numerous domains, demonstrating the versatility and power of hybrid generative models. Here, we explore several critical applications that highlight the transformative potential of VAE-GAN models.

3.1. Art and Creative Media

In the realm of creative media, VAE-GANs have significantly transformed artistic creation, offering artists and designers unprecedented tools for content generation [19]. These models excel in synthesizing and manipulating digital images, allowing for the creation of complex and unique artworks that reflect nuanced artistic intents [20]. For example, VAE-GANs have been used to develop systems that mimic the styles of historical painters and blend multiple styles to create innovative artworks [20]. Such capabilities have empowered artists to explore new creative horizons, making art more accessible and customizable. One notable application involves a system that dynamically generates artwork for digital platforms, where users can specify style and thematic elements, resulting in personalized art pieces that cater to individual tastes [20].

3.2. Medical Imaging

VAE-GANs play a critical role in medical imaging, significantly enhancing the field's capacity for training and research [21]. These models are adept at generating anatomically accurate, synthetic medical images replicating various pathological conditions, which are invaluable for training medical professionals without compromising patient privacy [22]. By improving the resolution and clarity of these synthetic images, VAE-GANs facilitate more accurate diagnostics and treatment planning [22]. For instance, VAE-GANs have been employed in radiology to produce high-resolution images of rare tumors, aiding in developing more effective diagnostic procedures and treatments [22].

3.3. Personalized E-commerce

In the e-commerce sector, VAE-GANs are revolutionizing how consumers interact with products online by personalizing the shopping experience at an unprecedented scale [23]. These models dynamically generate images of products in various styles and configurations, allowing customers to visualize products in a highly customized manner [24]. A prominent study by Kim and Lee (2023) highlighted how VAE-GANs enabled the dynamic visualization of furniture in different room settings, significantly enhancing customer decision-making processes. This capability led to a notable 30% increase in user engagement and a 25% rise in sales conversions, as consumers could better envision how the products would fit into their personal spaces [23]. This application not only boosts consumer satisfaction but also aids retailers in understanding consumer preferences more deeply, enabling more targeted marketing and inventory management [23].

3.4. Video Game Development

VAE-GANs also significantly impact the video game industry by enhancing how game environments and elements are created and interacted with [25]. These models facilitate the dynamic generation of detailed and responsive game environments that adapt to player actions and preferences in real-time, thus providing a unique and immersive gaming experience [6]. For example, VAE-GAN technology

has been used to develop adaptive difficulty levels and game narratives that change based on the player's style and progress, which keeps the gameplay engaging and challenging [6]. Furthermore, by automating part of the content creation process, VAE-GANs reduce the workload on game developers, enabling them to focus on more creative aspects of game design [26]. This technology enhances player engagement and streamlines the development process, allowing for the quicker release of more complex games.

3.5. Barriers to Widespread Adoption of VAE-GAN Technologies

Despite the vast potential of VAE-GAN applications across various fields, there are significant obstacles that currently limit their broader adoption. These include ethical implications of using these powerful generative models, particularly the risk of creating realistic yet potentially deceptive content. Such uses pose serious societal risks, necessitating vigorous efforts to develop rigorous ethical guidelines and robust regulatory frameworks to mitigate these risks. Additionally, the high computational demands of training VAE-GANs restrict their accessibility, especially for researchers and developers with limited resources. Ongoing research is dedicated to optimizing these models to reduce computational overhead, making them more sustainable and widely accessible.

4. Discussion

The integration of VAEs and GANs has undoubtedly pushed the boundaries of what is achievable with generative models. However, several significant challenges remain, which could dictate future research trajectory in this field.

4.1. Training Stability and Model Robustness

The integration of VAEs and GANs into VAE-GAN models significantly advances the field of generative modeling, providing enhanced capabilities and pushing the boundaries of what these technologies can achieve [8]. While this integration offers new possibilities, it also brings forward the inherent challenges associated with each component model, particularly concerning training stability and robustness [27].

The adversarial nature of GANs contributes to a known challenge called mode collapse, where the generator might not capture the diversity of input data adequately, resulting in less variability in the outputs [27]. Although the VAEs component in VAE-GAN models helps to structure the latent space more effectively, potentially mitigating some of the risks associated with mode collapse by providing more controlled input for the GANs part, it does not completely eliminate this issue. Moreover, VAEs themselves can suffer from 'posterior collapse,' where they fail to fully utilize the encoded information in the latent space, thus not capturing the full potential of the data [28].

Addressing these complex challenges is crucial for enhancing the overall reliability and utility of VAE-GANs models. Current research efforts are increasingly focused on developing innovative training methods that not only promote stability but also improve the robustness of these hybrid models [29]. These methods include advanced stabilization techniques, such as tailored loss functions and strategic training interventions, which are designed to ensure more consistent learning outcomes and prevent the dominance of unhelpful patterns in the training process [30].

4.2. Ethical Considerations and Misuse

The potential for misuse of VAE-GANs presents significant ethical considerations [31]. The ability of these models to generate realistic data opens up possibilities for misuse, particularly in the creation of deepfakes, misinformation, or other deceptive media forms [31]. Such applications pose grave risks, potentially undermining public trust and infringing individual rights [32]. Stringent ethical guidelines and robust regulatory measures must accompany the development of VAE-GAN technologies [33]. These frameworks must keep pace with technological advancements to mitigate the risks associated with their misuse [33]. Efforts must include multi-stakeholder engagement to formulate policies that

ensure ethical usage and prevent harm, reinforcing the accountability of developers and users alike [32].

4.3. Computational Efficiency

Another significant challenge facing VAE-GANs is the computational demand to train these complex models, which often necessitates extensive resources [34]. This requirement can limit accessibility for researchers and developers who do not have access to high-power computing facilities, potentially stifling innovation and democratization of this powerful technology [35]. To overcome this barrier, ongoing research is focused on enhancing the computational efficiency of VAE-GAN models [35]. Innovations are needed in the models, training procedures, and hardware optimization to make these technologies more sustainable and accessible to a broader audience [17]. Developing lightweight models and employing efficient training algorithms are critical areas of focus that can help reduce the resource intensity of VAE-GAN applications [17].

4.4. Expanding Application Domains

The application domains for VAE-GANs are rapidly expanding, opening new avenues for research and practical implementation. These models hold particular promise in fields such as augmented reality, personalized medicine, and autonomous systems, where the enhanced capabilities of generative models can significantly impact. For instance, VAE-GANs could revolutionize user interaction in augmented reality by seamlessly integrating realistic, AI-generated images into live environments, enhancing the immersive experience [36]. In personalized medicine, these models can synthesize patient-specific data, aiding in tailored treatment planning and simulation without data availability constraints [36]. Additionally, the potential for VAE-GANs to generate dynamic environments in real-time makes them highly valuable for developing autonomous systems, where adapting to changing conditions is crucial [36]. Tailoring these technologies to specific industry needs could catalyze breakthroughs, transforming how sectors leverage AI to solve complex challenges.

4.5. Future Research Directions

Looking ahead, the trajectory of future research in VAE-GANs is set to address several critical areas to enhance their applicability and resolve existing challenges. Developing more stable training algorithms remains a priority, focusing on novel architectural solutions that prevent mode and posterior collapse [29]. Research into alternative network architectures that optimize the balance between data diversity and model stability is vital for advancing these models' effectiveness and reliability [30]. Moreover, creating more efficient models that reduce computational costs is essential. This includes advances in algorithm efficiency, lighter network designs, and better resource management, making VAE-GANs more accessible and practical for wider adoption [30]. Additionally, establishing robust ethical standards and regulatory frameworks is imperative as these technologies become more integrated into societal applications. Collaborative efforts between developers, policymakers, and ethical experts are necessary to ensure that the expansion of VAE-GAN applications aligns with societal values and benefits humanity as a whole.

5. Conclusion

Our review has comprehensively addressed the strategic integration of VAEs and GANs, a synergy that significantly advances the capabilities of generative models. These hybrid VAE-GAN models effectively surmount numerous limitations previously faced by their component technologies, thus broadening the horizons for their application across various industries. By merging the probabilistic depth and encoding accuracy of VAEs with the high-resolution and realistic generation capabilities of GANs, VAE-GANs have profoundly transformed sectors such as the creative arts, medical imaging, e-commerce, and video game development.

Despite the remarkable advancements facilitated by VAE-GANs, persistent challenges related to training stability, model robustness, and ethical considerations continue to shape the research and

development trajectory in this field. The capacity of these models to generate highly realistic data raises significant ethical concerns, particularly regarding the potential for misuse in creating deceptive content like deepfakes. Addressing these challenges necessitates the formulation of stringent ethical guidelines and robust regulatory frameworks.

Looking forward, research in VAE-GANs is set to focus on developing more stable training algorithms, optimizing architectural designs, and reducing computational costs to enable broader adoption and application. As these technologies extend into new domains such as augmented reality and personalized medicine, they are expected to catalyze innovative breakthroughs that redefine how industries leverage artificial intelligence.

Continued vigilance and responsible advancement are imperative as VAE-GAN technologies evolve, ensuring that their development is guided by a firm commitment to ethical standards and a focus on generating positive societal impacts. The ongoing refinement of these models promises not only to push the boundaries of technological innovation but also to do so in ways that benefit society at large.

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