What should GAN in AI stand for?

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***Abstract*—GANs were introduced as an AI framework where two learning models (a generator and a discriminator) compete in a zero-sum, two-player game. Initially, GANs were applied in adversarial machine learning such as deepfakes for images, audio, and videos used in digital media so the name Generative Adversarial Networks was coined.**

While early research on GANs focused on adversarial applications, a diverse range of non-adversarial GAN applications soon emerged. It is to be noted that the GAN formulation is inherently neutral, specific application makes it adversarial. Accordingly, we argue that an appropriate interpretation of GAN should be ”Generative Associated Networks” since it tries to associate a generated instance to the real one by minimizing their divergence. This misnomer correction is needed as GANs (based on their defining characteristics) are generating synthetic data, hyper-realistic images, videos, and other transformative digital content. Their influence extends across domains such as healthcare, art, and data augmentation, making this technique useful in many AI applications. Given this evolution, we feel that GAN should stand for “Generative Associated Networks”, reflecting their broader role in generating and associating meaningful representations beyond adversarial learning.

I. Introduction

In 2014, Ian Goodfellow et al. [9] introduced Generative Adversarial Networks (GANs), where a generator tries to misguide a discriminator in different ways to make wrong decisions (as illustrated in Figure 1).

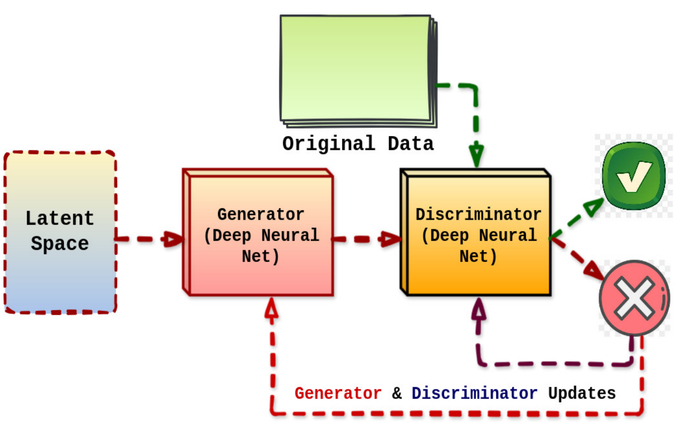

Fig. 1. Conceptual block diagram of Generative Adversarial Networks.

Initially, GANs have been used for adversarial applications, including data manipulation or poisoning AI-based systems, which could compromise machine learning models. The rise of AI-generated synthetic faces, image morphing, voice cloning, and fake video creations facilitated digital deception such as identity fraud and deepfake proliferation, making social engineering attacks highly sophisticated. Furthermore, these are often disseminated through social media and amplified by text narratives to mislead and influence public opinion on politics and social issues. Such applications of GAN serve as catalysts for adversarial manipulation and digital impersonation.

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II. Why Generative Associative Networks?

GANs have traditionally been framed as adversarial systems where a generator and a discriminator compete in a zero-sum game [17], [22].

Mathematically, GANs describe training a discriminator to classify or recognize digital entities, while a generator attempts finding similar entities using various distance measures. This iterative training process continues until the generator produces data that is indistinguishable from real data. However, this perspective constrains the broader understanding of GANs as fundamentally generative and associative systems rather than merely adversarial constructs. We propose redefining GANs as Generative Associative Networks, shifting the focus from adversarial learning to directed associative learning, where the generator establishes a deep correspondence between latent representations and data variants.

At its core, a GAN is a high-dimensional transformation function that maps latent structures to data distributions, a process inherently connected to an optimization heuristic for a generative modeling. By re-framing GANs through an associative lens, we recognize their ability to capture, encode, and reconstruct application-specific patterns or objects. This redefinition not only aligns with the true generative essence of GANs but also paves the way for their meaningful use.

A. Mathematical Formalization of GAN

Traditional GANs [9], [17], [19] employ discriminators $f_w\colon \mathscr{X} \to [0,1]$ as parametric classifiers (e.g., SVMs, MLPs) with fixed capacity to distinguish real data X from generated samples $\mathscr{G}_\theta(Z)$ in data space $\mathscr{X}$. The generator $\mathscr{G}_\theta\colon \mathscr{Z} \mapsto \mathscr{X}$ maps latent variables $Z \in \mathscr{Z}$ to structured data representations. A non-parametric formulation—where both the generator and discriminator dynamically adapt their representation landscape—eliminates rigid model assumptions, allowing them to self-adjust based on the intricacy of the data manifold. This approach significantly improves *expressivity* ($\mathscr{G}_\theta$ can better approximate complex, multi-modal distributions),

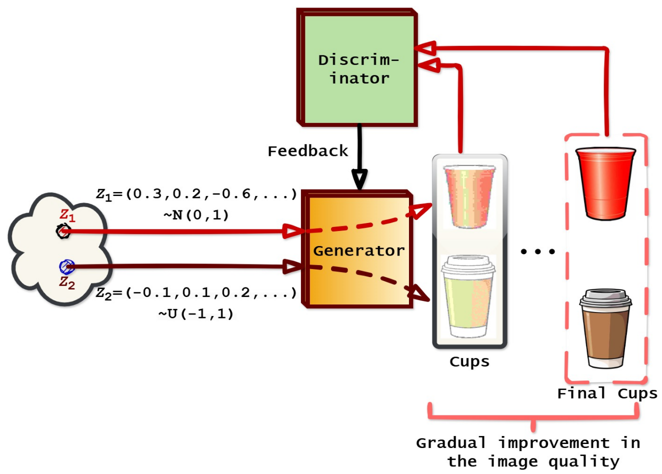

Fig. 2. Illustration of generic GANs with cup images, created by the noise samples following different distributions. It highlighted the gradual modifications in the image (variants) via the discriminator's feedback over many iterations.

generalization (f_w refines decision boundaries dynamically, capturing subtle variations in high-dimensional data), and *robustness* (model resists adversarial perturbations and adapts to shifts in heterogeneous distributions) as illustrated in Fig. 2.

Basic-GANs [9], [17], [19] compute the discrepancy between $\mathbb{X}$ and $\mathscr{G}_\theta(\mathcal{Z})$ using divergence measuring functions $\mathscr{E}\colon \mathscr{X} \times \mathscr{G}_\theta(\mathscr{Z}) \mapsto \mathbb{R}$, mainly JS. f_w are mostly trained using real data samples $X \in \mathscr{X}$ and distinguishes samples of $\mathbb{X}$ from $\mathscr{G}_\theta(\mathcal{Z})$. Basic-GANs often rely on maximizing likelihood, or equivalently minimizing the relatively unstable JS-divergence between $\mathbb{X}$ and $\mathscr{G}_\theta(\mathcal{Z})$. The objective (cross-entropy cost function) of the Basic-GANs can be defined in terms of discrepancy as follows:

$$\mathscr{E}\left(\mathbb{X}, \mathscr{G}_\theta(\mathcal{Z})\right) = \max_w \mathbb{E}\left[\log f_w(X) + \log(1 - f_w(\mathscr{G}_\theta(Z)))\right] \tag{1}$$

where $X \sim \mathbb{X}$, $Z \sim \mathcal{Z}$ and $\mathscr{G}_\theta$ tries to match f_w and minimizes the power of two-sample test, i.e., minimizes (a logistic surrogate for) the accuracy of f_w. Again, optimizing w maximizes the probability of distinguishing samples from $\mathbb{X}$ and $\mathscr{G}_\theta(\mathcal{Z})$. Accordingly, GAN loss function can be written as follows**:**

$$\min_\theta \max_w \mathbb{E}_{X\sim\mathbb{X}}\left[\log f_w(X)\right] + \mathbb{E}_{Z\sim\mathcal{Z}}\left[\log\left(1 - f_w(\mathscr{G}_\theta(Z))\right)\right] \tag{2}$$

The generator's main objective is to map a noise distribution to the real data space, while the discriminator continuously refines its classification boundaries. The nature of this formulation stems from the fact that the discriminator and the generator have competitive objectives, with the generator creating variations of something (through diffusion or adding noise) and the discriminator aiming to judge the creation accuracy between real and its variants. This formulation implies that progress is purely driven by the discriminator feedback loop during the learning process. Fig. 3 gives an example of the generator training through indirect feedback (gradients propagated through the discriminator rather than explicitly learning structured latent-to-data correspondences.

Accordingly, GANs are better understood as associative systems that learn structured mappings between latent variables and data distributions. This is evident while analyzing GAN learning through the lenses of optimal transport and mutual information.

III. Non-Adversarial GANs & their Applications

As already discussed, the GANs' fundamental ability to learn complex data distributions, enabling diverse non-adversarial applications across various domain.

A. Disentangled Representation GANs (DisGANs)

Disentangled representation learning is a fundamental pursuit aiming to decompose complex data distributions into independent and semantically meaningful factors. Traditional deep learning models struggle to achieve this level of interpretability due to the entanglement of latent variables. However, DisGANs (InfoGAN [4] and β-VAE-GAN hybrids [11]) have emerged as a powerful paradigm to address this challenge by leveraging competitive training in conjunction with unsupervised information-theoretic constraints.

Mathematically, InfoGAN [4] extends the standard GAN objective by incorporating an auxiliary distribution $Q\left(C \mid X\right)$ that approximates the posterior $P\left(C \mid X\right)$, enforcing a structured latent space:

$$\mathscr{L}_{\text{Info}} = \mathscr{L}_{\text{GAN}} - \lambda \mathscr{I}\left(C, \mathscr{G}_\theta(Z, C)\right), \tag{3}$$

where $\mathscr{I}\left(C, \mathscr{G}_\theta(Z, C)\right)$ is the mutual information between the latent code C and the generated sample $\mathscr{G}(Z, C)$. This forces the generator to encode interpretable features in distinct dimensions of the latent space.

Applications of DisGANs in High-Impact Domains: By learning disentangled and interpretable latent representations, DisGANs have revolutionized several key areas of AI and ML:

- *Neuroscience: Brain Signal Decomposition*: Brain activity data, such as EEG and fMRI signals, are often high-dimensional and complex. DisGANs decompose these signals into independent cognitive processes, enabling improved brain-computer interfaces and neurological disorder diagnosis [2], [7]. For instance, disentangling motor movement patterns from noise in EEG signals aids in the development of real-time brain-controlled prosthetics.
- *Medical Imaging: Lesion Disentanglement*: Traditional medical imaging analysis struggles with the entanglement of pathological and anatomical variations in data. DisGANs enable the separation of lesion information from normal tissue structure, significantly improving automated disease diagnosis. In cancer imaging, DisGANs isolate tumor features from patient-specific anatomical variations, enhancing diagnostic accuracy in MRI and CT scans.
- *Robotics: Pose and Motion Learning*: DisGANs provide a structured representation of human motion and robotic kinematics, essential for real-time control, motion

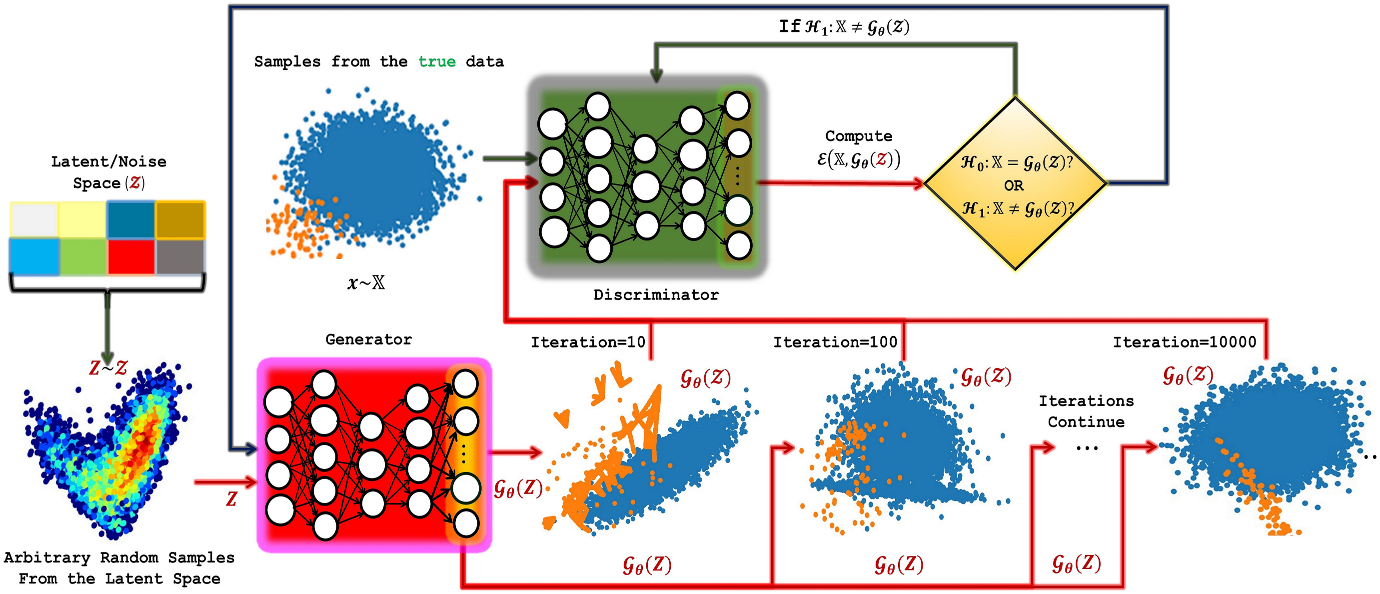

Fig. 3. Generator distribution change over the iterations: This diagram shows the gradual improvement of the generator distribution (and subsequent outputs) over the iterations after getting meaningful structured feedback from the discriminator.

prediction, and simulation-to-reality transfer in robotics. By disentangling pose (static) from motion (dynamic) components, DisGANs improve the generalization of reinforcement learning models in robotic grasping and locomotion tasks.

B. Explainable AI GANs (XAI-GANs)

As deep learning systems become increasingly complex, the need for transparent, interpretable, and trustworthy AI has never been more critical. Black-box models, particularly in high-stakes applications such as medicine, finance, and law, often lack explainability, making their decisions difficult to audit, trust, or validate. This opacity raises concerns about bias, fairness, and accountability in AI-driven decision-making. In response, Explainable AI GANs (XAI-GANs, such as Counterfactual-GAN [13], [28], Attribution-GAN [1], Explanatory-GAN [26]) have emerged as a transformative approach to bridging the gap between deep learning's predictive power and human interpretability. Unlike traditional GANs, which prioritize realism in data generation, XAI-GANs introduce semantic clarity and interpretability by generating counterfactual examples, visualizing decision boundaries, and attributing model decisions to human-understandable features.

Mathematically, XAI-GAN framework incorporates an explainability constraint:

$$\mathscr{L}_{\text{XAI}} = \mathscr{L}_{\text{GAN}} + \lambda \mathscr{L}_{\text{exp}}, \tag{4}$$

where $\mathscr{L}_{exp}$ is an additional explainability term that enforces counterfactual validity, feature attribution, or decision-boundary visualization.

Application Areas of XAI-GANs: By integrating adversarial learning with explainable AI techniques, XAI-GANs address fundamental challenges in AI fairness, interpretability, and accountability across multiple domains:

- *Bias Detection and Fairness-Aware AI*: Deep learning models often exhibit hidden biases, disproportionately affecting underrepresented groups. Counterfactual-GANs generate synthetic diverse demographic variations, helping to detect and mitigate biases in models used for hiring, credit scoring, and criminal justice. For example, if a financial model systematically denies loans to applicants from a specific demographic, an XAI-GAN can generate counterfactual applicants with minimally altered attributes (e.g., income, credit history) to expose discriminatory decision boundaries.
- *Interpretable Medical Diagnostics*: Black-box models in healthcare lack transparency, limiting adoption in disease diagnosis and treatment planning. Attribution-GANs highlight which biomarkers or medical imaging features contribute most to diagnoses, enabling clinicians to validate AI-generated decisions. For example, in oncology, Explanatory-GANs help radiologists understand why a model predicts malignancy in a tumor by identifying key MRI regions responsible for the decision.
- *Trustworthy AI for Autonomous Systems*: Autonomous vehicles and AI-powered decision-making systems require interpretable models to ensure safety and reliability. Explanatory-GANs generate visual representations of autonomous driving decisions, helping engineers audit how models respond to changing traffic conditions, adversarial perturbations, or sensor failures.

C. Cross-Domain Generalization GANs (XDG-GANs)

Cross-Domain Generalization GANs (XDG-GANs) excel in scenarios where vastly different domains require unsupervised knowledge transfer without explicit paired mappings. Unlike conventional transfer learning methods that assume some shared structure, XDG-GANs discover complex correspondences across heterogeneous domains. Key mechanisms form of XDG-GANs includes: (i) *Cycle-Consistency Regularization* ($\mathscr{L}_{\text{Cyc}}$) ensures bidirectional mapping between domains, preventing mode collapse [5], [23]; and (ii) *Semantic Feature Alignment* leverages adversarial training to bridge distribution gaps, enabling transfer across highly disparate domains.

Applications of XDG-GANs includes: (i) *Remote Sensing & Geospatial Intelligence*: CycleGAN-based models [3], [32] transform satellite imagery into high-resolution aerial views for better environmental monitoring and urban planning. Multi-Sensor Data Fusion GANs integrate SAR (Synthetic Aperture Radar) and optical images, overcoming weather-related limitations in remote sensing. (ii) *Medical Imaging & Computational Biology*: XDG-GANs enhance generalization in medical segmentation tasks (e.g., CT-to-MRI translation [23]), addressing modality gaps in tumor detection and organ segmentation. (iii) *Climate Science Environmental Modeling*: GAN-based models [16] learn mappings between oceanic temperature patterns and atmospheric changes, improving climate forecasting accuracy. (iv) *Autonomous Driving & Sim-to-Real Adaptation*: GANs bridge the sim-to-real gap, allowing models trained in synthetic environments to generalize in real-world driving scenarios [18].

1) Low-Resource Adaptation GANs (LRA-GANs): While XDG-GANs focus on domain shifts, Low-Resource Adaptation GANs (LRA-GANs) tackle data scarcity by transferring knowledge from high-resource to low-resource domains. Unlike standard few-shot learning, which depends on meta-learning, LRA-GANs synthesize diverse, high-fidelity samples to improve generalization. Key mechanisms of LRA-GANs include (i) Few-shot GANs [12], [21] create realistic high-variation samples using only a handful of training examples. (ii) MetaGANs [31] optimize the GAN architecture to rapidly adapt across unseen domains.

Applications of LRA-GANs include: (i) *Low-Resource Language Processing*: GANs synthesize realistic speech [27], text [10], and handwriting samples [8] to enhance low-resource NLP applications (e.g., underrepresented languages). (ii) *Precision Medicine & Rare Disease Diagnosis*: LRA-GANs create synthetic patient data to augment training datasets for rare diseases, improving predictive accuracy in scenarios with minimal real-world examples. (iii) *Personalized Federated Learning*: In federated settings, where data is heterogeneously distributed, LRA-GANs mitigate client-side data scarcity by transferring domain-specific knowledge.

In short, DA-TL GANs emphasize knowledge transfer over adversarial learning, making them more appropriately classified as Generative Associative Networks—systems that associate structured knowledge across domains instead of merely generating synthetic data.

D. Scientific Discovery and High-Fidelity Data Simulation

GANs have become indispensable in scientific simulations, accelerating research in physics, biology, and chemistry by generating high-fidelity synthetic data that approximates real-world phenomena.

1) Physics-Informed GANs (PhysGANs): Such GANs (Physics-Informed Neural Network GAN or PINN-GAN [6]) generate physically plausible simulations by embedding domain-specific constraints in the generative process. Its applications include quantum mechanics (wavefunction generation), fluid dynamics (turbulence modeling), materials science (crystal structure prediction).

2) Biological Sequence GANs (BioGANs): Such GANs (SeqGAN or Sequence modeling GAN [30], ProteinGAN [20]) models biological sequences such as DNA, proteins, and cell structures. The applications are mostly on drug discovery [15], genomics [30], protein folding prediction [20].

E. Robust Anomaly Detection and Security GANs

Rather than serving adversarial purposes, GANs can enhance cybersecurity by learning normal patterns and detecting deviations in real-world data distributions.

1) Industrial Anomaly Detection GANs (IAD-GANs): Here, the objectives are to detect system failures, manufacturing defects, and infrastructure anomalies. The applications of such GANs include smart manufacturing (defect detection), predictive maintenance (sensor-based anomaly prediction), transportation safety. A few such types of GANs include AnoGAN (Anomaly Detection GAN) [25], AD-GAN [29].

2) Network Security GANs (NetSec-GANs): Here, the objectives include identifying and preventing cyberattacks by modeling normal network behaviors and detecting adversarial anomalies. Applications include intrusion detection, phishing prevention, denial-of-service (DoS) attack mitigation. A few such types of GANs include CyberGAN [14], Intrusion-GAN [24].

This taxonomy establishes a structured perspective on GANs that goes beyond adversarial interpretations, positioning them as Generative Associative Networks—models that excel at learning deep associations between latent spaces and data distributions. The adversarial component is merely a tool, not a defining characteristic. By redefining GANs under this taxonomy, we enable a shift in research focus toward their non-adversarial capabilities, paving the way for advancements in privacy-preserving AI, scientific modeling, explainability, and security.

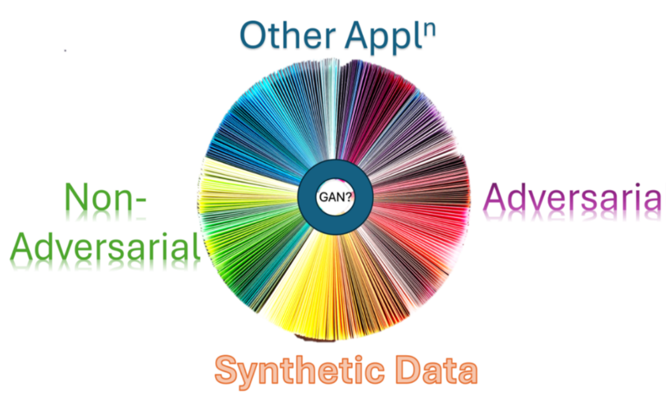

Fig. 4. Different application domains of Generative Associated Networks (GANs).

IV. Concluding Remarks

This review paper tries to shade light on the misnomer of GAN terminology, which we argue should be a Generative Associated Network based on its theoretical formulation and technological interpretation. There is nothing in the GAN formulation, which makes it only an adversary technique. This argument is also true for all AI techniques since these can be used with varying intend. As many variants of GAN are successfully being used both in adversarial and non-adversarial applications (Fig. 4), we feel that this correction will be essential for future research and developments.

In conclusion, "Generative Associative Network" better encapsulates the broader, constructive and evolving role of GANs, moving beyond their initial adversarial framework, towards a more holistic understanding of generative modeling. This perspective not only enhances their applicability in ethical AI but also aligns GAN research with pressing challenges in federated learning, decentralized intelligence, and privacy-preserving machine learning.

Renaming of GANs as Generative Associative Networks accurately justify their role as intelligent latent-structure learners, positioning them at the core of next-generation AI models for science, medicine, and autonomous systems.

As GANs continue to advance, regulatory and ethical responsibility are essential to mitigate their adversarial risks while harnessing their transformative potential.

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