
On the Challenges and Opportunities in Generative AI

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Abstract

The field of deep generative modeling has grown rapidly and consistently over the years. With the availability of massive amounts of training data coupled with advances in scalable unsupervised learning paradigms, recent large-scale generative models show tremendous promise in synthesizing high-resolution images and text, as well as structured data such as videos and molecules. However, we argue that current large-scale generative AI models do not sufficiently address several fundamental issues that hinder their widespread adoption across domains. In this work, we aim to identify key unresolved challenges in modern generative AI paradigms that should be tackled to further enhance their capabilities, versatility, and reliability. By identifying these challenges, we aim to provide researchers with valuable insights for exploring fruitful research directions, thereby fostering the development of more robust and accessible generative AI solutions.

1 Introduction

Generative AI has recently gained unprecedented attention with the emergence of Large Language Models [LLMs; 19, 32, 138, 159] and their dialogue agents, such as ChatGPT [18] and LaMDA [203]. These works have demonstrated that scaling relatively simple generative models [211], exposing them to large amounts of data, and incorporating preferences via the form of human feedback [142, 255], yields immensely powerful AI tools that have the potential to impact society profoundly. In contrast to traditional discriminative ML learning tasks, the output space of generative AI is often high dimensional, leading to unique problems in regards to efficient inference, pruning, and quantization.

Fundamentally, LLMs model probability distributions over a discrete state space, i.e., text tokens. Analogously in the continuous domain, diffusion models [71, 191] have become the de-facto model family for high-quality image synthesis, surpassing generative adversarial networks [GANs; 58, 93, 176] and variational autoencoders [VAEs; 96, 166, 208]. Similar to LLMs, the combination of a simple model [187] coupled with a successful network architecture [43, 168], a large quantity of data, and human feedback in the form of text has led to breakthroughs in image synthesis tasks like

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large-scale text-to-image generation [162, 167, 171]. However, the impact of generative AI extends far beyond text and image generation and across diverse research domains, spanning from biology [88] to weather forecasting [163]. Within an array of applications—ranging from code generation [28, 112] to video creation [236, 73, 184, 17], audio synthesis [14, 117], and even artistic and musical composition [77]—we witness a consistent acceleration of generative AI-driven progress.

With the current advancements and excitement surrounding generative AI, a question naturally arises: Are we on the brink of an AI utopia? Are we close to defining a *perfect generative model*—capable of modeling (i) any joint and conditional distribution over real-world data and (ii) its underlying causal structure—that could theoretically solve every conceivable AI task, from discriminative challenges to reinforcement learning and beyond? We believe the answer, however, is a resounding no. The realization of such a model, one that would fundamentally transform the field of AI, is still a distant vision, hampered by substantial theoretical, practical, and ethical challenges.

We argue that scaling up current paradigms is *not* the ultimate solution in isolation and that the current state of generative AI falls short of the efficiency, inclusivity, transparency, and overall usability required for its widespread integration across domains, particularly in high-stakes decision problems. We, therefore, collected views and opinions from different communities to identify key unresolved challenges and to guide future research towards what we perceive are the most critical and promising areas. More specifically, we discuss key challenges in (a) broadening the *scope and adaptability* of Deep Generative Models (DGMs)³ by overcoming current limitations and providing an outlook on promising, and largely unexplored research directions (Section 2); (b) improving their *efficiency and resource utilization*, to lower the memory and computational requirements and enhance accessibility and sustainability in their adoption (Section 3); and, finally, addressing *ethical and societal concerns* that are crucial for responsible deployment (Section 4).

This paper emerged as a result of the Dagstuhl Seminar on *Challenges and Perspectives in Deep Generative Modeling*⁴, held in Spring 2023. Our goal is to provide an overview of research and development priorities to guide the forthcoming research toward areas of significant potential impact. By outlining a comprehensive roadmap, we hope to empower researchers and practitioners alike, fostering the development of generative AI models that are not only more robust and reliable but also accessible to a wider audience.

2 Expanding Scope and Adaptability

While remarkable progress has been made by scaling DGMs to massive datasets and model sizes (for instance, in text and high-resolution image synthesis), we argue that true innovation extends beyond this achievement. It is crucial to move beyond evaluations that rely exclusively on state-of-the-art leaderboard rankings [10] and understand these models’ inherent and often hidden constraints [137]. This section analyzes some of these challenges in the context of large-scale DGMs from the lens of their generalization capabilities (Section 2.1) and the lack of transparency in their underlying modeling assumptions (Section 2.2). We examine these fundamental challenges and provide research directions that could broaden the adaptability of DGMs to promote long-term progress in the field.

We also explore two promising avenues that have the potential to greatly enhance the scope of generative models: (i) integrating causal representation learning (Section 2.3) and (ii) the development of a versatile, generalist agent capable of handling heterogeneous data types (Section 2.4).

2.1 Generalization and Robustness

To ensure reliability across various domains, DGMs must generalize effectively to shifts in data [out-of-distribution (OOD) robustness; 8, 9, 158, 224, 156] and be resilient to minor variations in input [adversarial robustness; 119]. Without proper generalization, generative models may produce

³In this paper, we refer to Generative AI as a collection of large-scale DGMs and use the term DGM henceforth.

⁴<https://www.dagstuhl.de/23072>

unrealistic or biased outputs, limiting their practical utility and trustworthiness in real-world applications [3].

Large-scale generative models trained on a wide variety of data show promise in achieving OOD robustness [215]. However, these models still face challenges in accurately capturing rare events, a difficulty that lies in effectively modeling the *long tail* of information [92]. This limitation indicates a gap in their ability to fully represent the vast and diverse spectrum of real-world scenarios, especially those that are less common but equally significant. Retrieval-augmented language models represent a promising direction to improve rare fact learning and go beyond scaling up datasets [92].

DGMs are also prone to adversarial vulnerability, often due to the presence of highly predictive but non-robust features that are used as a *shortcut* for prediction [45, 157, 219]. This poses a significant threat to various downstream scenarios, especially those of safety-critical applications [155, 215]. Several approaches to mitigate the effect of shortcut learning are based on dataset refinement, also known as data-centric approaches [225], or on model refinement. In the latter, work has been done towards improving robustness via adversarial training [256], ensembling [33], contrastive learning [30], and the direct integration of prior knowledge [79].

In the majority of applications, however, foundation models are often adapted to specific tasks and downstream datasets. Standard fine-tuning techniques often overemphasize the target task, leading to catastrophic forgetting [201] and a loss in the general robustness of the upstream model [198]. Therefore, a significant challenge is to develop robust adaptation methods that adequately solve the target task but still maintain the beneficial robustness properties of the upstream model (e.g., robustness to distribution shifts of the target dataset) [7, 45, 65, 120]. Additionally, the economization of the inference and memory cost of DGMs requires the distillation of large foundation models into smaller and cheaper models. In this context, it is important to develop robust distillation methods that do not sacrifice the robustness of the model [46, 254]. Overall, attaining models that are robust and interpretable will require explicitly encoding human priors into the training process [79].

2.2 Overcoming Implicit Assumptions

Silent Assumptions. Current generative models often rely on implicit assumptions and inductive biases that are rarely questioned or investigated in detail [246]. For example, while data are often assumed to be drawn independently, they are often correlated, such as in time-series data or through repeated measurements or related individuals. Traditional statistical methods commonly model data dependencies with random effects [85] or latent variables. In normalizing flows, dependencies can be incorporated directly into the likelihood objective [98], an approach that might be extended to other probabilistic approaches such as VAEs and diffusion models [199]. It is also possible to directly model latent variables leading to data dependencies with causal models [149].

We argue that it is important to scrutinize commonly overlooked assumptions in generative models that are silently accepted but may require a more in-depth investigation. For example, most generative models assume that latent distributions can be modeled on simple topological structures, while they might actually benefit from more expressive approaches [195]. Assumptions on noise and latent distributions also usually follow out of convenience and may hinder proper data fit for certain target distributions. An example is given by heavy-tailed distributions, which are addressed by only a few principled generative approaches so far [114, 103, 78].

The impact of model misspecifications in traditional statistical analyses can be immense [21], while the impact on downstream applications in DGMs still needs to be thoroughly explored. Models that rely heavily on the training data distribution may exhibit bias and decreased performance if not properly corrected by meaningful modeling assumptions [50].

Incorporation of Prior Knowledge. Recent major breakthroughs in deep generative models (DGMs) have primarily been achieved in settings where models could be trained on internet-scale data [138, 167]. However, many real-world applications, such as drug design [210], material engineering [221], personalized medicine [125], and protein biochemistry [12], often have much smaller datasets due to the high cost of data generation. In these areas, domain experts often possess troves of detailed prior knowledge, often filling entire textbooks, raising the question of whether this prior knowledge could be used to enable more data-efficient learning in generative AI models.

Indeed, it has been shown in the context of VAEs that incorporating domain prior knowledge can significantly improve model performance [52, 83] and even unlock their use for tasks that were previously impossible [51, 126, 127]. However, this relied on the fact that VAEs are Bayesian models and, therefore, offer a natural paradigm for specifying a prior distribution over their latent space.

Specifying priors for diffusion models is less straightforward than for VAEs. While it might seem at first glance that the Gaussian sampling distribution of the diffusion process is equivalent to the Gaussian latent prior in a VAE, in the diffusion case, it arises from the central limit theorem. This distribution is not easily changed, even for Gaussian diffusion noise or any finite-variance additive noise [192]. Recent works have attempted to enhance the space of diffusions through auxiliary dimensions [144, 185]. Moreover, mixing in many existing diffusion models breaks the relationship between the Gaussian sampling distribution and the observed sample space. Existing attempts to imbue diffusion models with novel priors have therefore sought to at least change the mean and covariance of the latent Gaussian by adding deterministic drift terms to the diffusion process [62, 105] or to replace parts of the process with a normalizing flow [240]. Unfortunately, neither of those approaches offers nearly the same flexibility of prior specification as the Bayesian priors in the latent space of VAEs, so further research into priors for diffusion models is sorely needed.

2.3 Causal Representations

Going beyond learning mere statistical correlations and understanding how underlying factors influence the generative process is the main objective of learning a causal representation of data [151]. Such representation can be used to reason about hypothetical scenarios in the world, understand the effect of interventions, and perform counterfactuals [150], thus facilitating informed decision-making. Although there have been attempts to develop methods for learning the optimal generative structure of deep latent variable models from data [68, 128], current generative models often neglect the underlying causal dependencies in their generative processes, making them prone to shortcut learning and spurious associations [64, 99, 129].

Causal representation learning in deep generative models has the potential to offer distribution-shift robustness, fairness, and interpretability [99, 178, 218]. Current open challenges include, but are not limited to, scalable and robust causal discovery from observational data [165, 250, 133], identifiability of deep generative models under weaker forms of supervision [2, 122, 213], lack of benchmark datasets and metrics to evaluate counterfactual quality [134], strong assumptions that are often violated in real-world applications [99], and, finally, the integration of diffusion models, a field that is currently under-explored but has tremendous growth potential [132, 145, 174, 175]. We suggest that the integration of causal principles in DGMs could pave the way for the development of more robust, interpretable, and actionable generative AI systems [251].

2.4 Foundation Models for Heterogeneous Data Types

Large vision-language models (VLMs) have demonstrated significant capabilities in processing both textual and image data simultaneously [124, 55, 34]. However, as the scope of application widens to encompass a broader range of data modalities, a variety of challenges emerge. These challenges are particularly pronounced in specialized fields such as healthcare and chemistry [160, 100].

In healthcare, generation based on diverse data types—including imaging, health records, and genomics—poses challenges in interoperability, data privacy, and security [135]. Time series generation, particularly, requires addressing irregularly sampled data, missing values, seasonality, and long-term dependencies [194]. In chemistry, physics, and chemical engineering, generative models have huge potential, not just for molecule, drug, and material design, but also in data augmentation, property prediction, and reaction prediction [227, 1, 25, 76]. Data in these fields are often sparse, heterogeneous, correlated, and have high uncertainties. On the other hand, they provide a vast body of physical and chemical domain knowledge, ranging from (strict) laws of nature and boundary conditions to (soft) empirical correlations and human experience. Therefore, developing hybrid (ML + domain knowledge) foundation models is a particular challenge [212, 87, 86, 75].

The overarching goal is to integrate information from diverse sources and understand complex relationships across different types of data [106, 164, 44]. However, to effectively interact with the physical world, embodied agents must integrate perception, reasoning, and planning across vision

and language, along with executing physical actions and environmental interactions. While datasets for natural language or images are relatively accessible [66, 107, 108], a comparable dataset for control tasks is lacking, suggesting generative simulation as a potential solution [230, 49].

3 Optimizing Efficiency and Resource Utilization

Efforts to scale deep generative models (DGMs) for tasks like language modeling and text-to-image synthesis often involve training large models with billions of parameters, which demands significant computational resources. This leads to practical issues such as high energy costs [228] and expensive inference, limiting access for many users. There is a clear need to reduce the memory and computational requirements of large-scale DGMs to enhance accessibility and sustainability [10].

In this context, we discuss the efficiency-related challenges in current DGMs. We focus on minimizing training and inference costs (Section 3.1), as well as highlighting challenges in designing evaluation metrics for DGMs (Section 3.2), which greatly affect the computational resources needed for model selection and tuning.

3.1 Efficient Training and Inference

Network Architecture. Optimizing the network architecture, which forms the backbone of modern machine learning, is crucial for efficient training and inference in DGMs. However, despite recent progress in improving LLMs [19], a principled investigation of the role of different underlying neural network modules is still lacking. For instance, several popular LLMs like PaLM [32] and LLaMA [205, 206] still largely reuse the original transformer architecture from Vaswani et al. [211] with some additional modifications [182, 196, 241]. However, the self-attention [5] operation in transformers traditionally scales quadratically in the context length, making inference computationally expensive, especially for long-context modeling. While recent work has focused on computationally improving attention mechanisms [200], these variants remain empirically ineffective at scale across domains. Therefore, exploring alternative autoregressive sequence-modeling frameworks with favorable properties, such as scalability and linear complexity in the context length, remains an interesting direction for future work [60, 61].

Similarly, several popular large-scale text-to-image diffusion models like DALL-E 2 [162] and StableDiffusion [167] largely reuse the popular UNet [168] backbone from Ho et al. [71], which has high memory costs. Therefore, we believe that a principled study of the impact of different network components in large-scale generative models is crucial for efficient training and inference. Some recent works [74, 95, 152, 153] already explore architectural design choices for reducing diffusion model sizes, thereby improving training dynamics while enabling faster inference with a lower memory footprint.

Model Quantization. The goal of model quantization is to reduce the precision of model weights and activations, enabling faster, memory-efficient training and inference, ideally without losing performance on downstream tasks. The most common quantization approaches are Post-Training Quantization (PTQ), which applies quantization to a pre-trained large model to enable faster and memory-efficient inference, and Quantization-Aware Training (QAT), which involves training a quantized model from scratch [101].

Despite some progress in developing PTQ and QAT methods for LLMs [37, 121, 231, 239] and large-scale text-to-image diffusion models [110], the existing methods are far from perfect. For instance, OPTQ [54], a PTQ-based approach, can perform inference for a quantized LLM (in this case OPT [244]) with 175B parameters on a single A100 GPU with 80GB of memory without degradation in accuracy. Though impressive, even this quantized model would likely have limited utility on a consumer-grade GPU device, let alone on standard edge devices. Similarly, QAT-based approaches can often achieve lower bitrates but trade off additional training for this efficiency. This can be a major computational bottleneck for large generative models. Therefore, we believe that investigating the impact of model quantization at low bitrates in large-scale generative models is a crucial direction for the practical deployment of these models.

Design Challenges. While currently dominant paradigms in generative modeling like diffusion models [71] and LLMs [19] exhibit excellent sample quality, there exist several crucial challenges

associated with the design of the generative process itself. For instance, the iterative nature of the multi-stage denoising process in diffusion models slows down inference considerably, often requiring hundreds to thousands of network function evaluations (NFE) to generate high-quality samples [71, 191]. Similarly, the autoregressive structure in LLMs can lead to slow inference due to sequential token generation. This is in contrast to alternative generative models like VAEs and GANs, which require only a single NFE but suffer from problems like blurry sample generation [42] and mode collapse [4].

Therefore, speeding up inference in diffusion models is a fundamental research problem spanning multiple (possibly complementary) directions. Some notable approaches include: developing training-free samplers [189, 118, 123, 243, 94, 146], designing better diffusion processes [185, 40, 144, 94], and combining other model families with diffusion models [145, 249, 232, 235]. Additionally, training a diffusion model in the latent space of a lossy transform [209, 167] not only improves memory requirements and sampling efficiency but also provides access to a more interpretable low-dimensional latent representation. A lossy transform (such as VQ-GAN [48]) can drastically reduce data dimensionality while retaining the perceptually relevant details of high-resolution images. Designing more efficient lossy compression operations in the context of diffusion models has received less attention in the community and is an important direction for further work [238, 67, 237]. However, despite these advances, sampling from diffusion models remains computationally challenging, typically requiring 25-50 NFEs to generate high-quality samples. While approaches based on progressive distillation [172, 130] can further speed up inference, they trade off additional training for faster sampling. Therefore, there is a need for DGMs that inherit all the advantages of diffusion models while supporting one-step sample generation by design (e.g., see consistency models [193, 190] for recent work in this direction).

For LLMs, in addition to an expensive self-attention operation in transformer-based autoregressive models, sequential token generation in a left-to-right fashion in these models makes inference more expensive. In contrast, diffusion models amortize the sequential generation cost among all tokens, leading to faster inference than their autoregressive counterparts. While this observation can potentially open up interesting research directions for sequence modeling using diffusion models [39, 229, 109], these approaches inherently lack the inductive bias for contextual generation, which has been shown to work well empirically for sequential modeling tasks. This affects their performance in downstream tasks that might require long-context modeling, such as video synthesis [236, 72]. While diffusion models can be incorporated within the autoregressive framework for such tasks, the resulting models can be very expensive during inference (due to the cost of synthesizing a single token using diffusion across multiple tokens). Therefore, we identify a potential tradeoff between long context modeling and efficient inference, with the diffusion and autoregressive modeling paradigms falling on the opposite ends of this tradeoff. Hence, designing generative modeling paradigms that can optimally balance this tradeoff remains challenging.

3.2 Evaluation Metrics

Evaluation metrics are crucial in guiding the research directions, as the conclusions derived from empirical studies are highly dependent on the chosen metrics for model comparison. In modern ML, evaluation metrics are a key component in hyperparameter tuning and model selection, affecting computational resources required during large-scale training. However, designing robust evaluation metrics for DGMs is challenging for several reasons.

Evaluation Metric Design. While likelihood-based metrics have been extensively used in evaluating DGMs, they do not guarantee a precise assessment of the quality of the generations [202]. Additionally, many popular generative models do not allow for tractable likelihood computation, so other evaluation metrics are necessary for evaluating the quality of generated images. For instance, in evaluating image synthesis models, several notable metrics, like the Fréchet inception distance [FID; 70], compare the distribution of the generated samples with the train/test data samples [173, 11]. However, these approaches are far from perfect. First, to compute these metrics, one generates a large set of samples (around 50k). This can be computationally demanding for generative models with a sequential inference process like diffusion and autoregressive models. Second, since these methods typically rely on a model pre-trained on ImageNet [35], they are more suited for evaluating generative models of natural images [102] and, therefore, might disregard important features in other domains, e.g., medical images.

Similar considerations are relevant for evaluating text generated from LLMs [139, 140]. While FID has also been adapted to measure the quality of generated text [179], the most popular metrics are based on n-gram matching such as BLEU [147], or ROUGE [116]. Additionally, Zhu et al. [253] proposes to complement BLEU with self-BLEU to promote diversity. However, there is often a quality-diversity tradeoff [20], where a model that generates high-quality text might have low diversity and vice versa.

Subjective aspects in generation. Another major challenge underlying the evaluation of generation quality is the subjective nature of sample attributes, such as realism and style (especially for multimedia data). For instance, while human inspection [36, 252] is typically the gold standard for evaluating generated images, human evaluators might have subjective opinions on what is considered realistic in the target domain (e.g., medical images or industrial optical inspection). This also holds for conditional synthesis tasks like text-to-image generation [161, 167, 171], where there is usually no reference distribution of real images. For this reason, a common approach is to set up a benchmark for evaluation based on human judgment [171, 81]. However, in many cases, human judges can disagree over which samples have better quality⁵. In addition, human evaluation focuses on individual images and does not necessarily measure how well the generative model reflects the data distribution. Therefore, since many desired properties of generative models cannot be evaluated programmatically, learning a reward function from human preferences has gained importance [142]. A public benchmark of the learned reward function would provide a useful evaluation suite for generative models.

Robustness. There is a pressing need to design robust evaluation metrics [139]. For instance, while commonly used in image synthesis, FID can be sensitive to minor perturbations in the input data [148] (see Chong and Forsyth [31] for additional discussion on sources of bias associated with FID and IS and Borji [13] for more related evaluation metrics). Similarly, in language modeling, expected calibration error [63] is also an evaluation metric of interest. While pre-trained large models are often well calibrated [138, 90], fine-tuning or RLHF often hurt calibration accuracy [204]. Evaluating issues in calibration [233] has led to work on mitigating these issues (e.g., Wang et al. [216] for fine-tuning and Tian et al. [204] for RLHF), highlighting the importance of robust evaluation.

Model Selection. Model selection is essential in training large-scale models but can be computationally expensive. While evaluation metrics with scaling laws are now used to predict early on in a training run whether it is likely to be successful [138], this can still be computationally inefficient. We also believe that more effort should be invested in analyzing the *performance-complexity* tradeoff, an important yet under-investigated measure for real-world applications at scale. This tradeoff refers to the balance between model performance and computational complexity, to identify the model families that lie in the associated Pareto set that optimizes this tradeoff [38, 15, 29, 16]. The naïve approach—training well-performing models in each class and computing their respective complexities—is time- and resource-intensive. Therefore, alternative evaluation metrics should be investigated by utilizing tools from information and learning theory [e.g., 234].

4 Ethical Deployment and Societal Impact

With the current excitement around the scope and application of large-scale generative models, we are also witnessing a growing apprehension, fueled by media reports, of adverse outcomes surrounding the rapid advancement of generative AI. These concerns add to the conceptual and practical considerations discussed so far, and encompass a range of issues, including the spread of misinformation, the absence of regulatory frameworks [131], unintended harm [59], and debates over open-source versus closed-source technologies [26], among others. Here we identify key challenges concerning the responsible deployment of large-scale deep generative models. More specifically, we discuss several aspects, including the dissemination of misinformation (Section 4.1), violation of privacy and copyright (Section 4.2), presence of biases (Section 4.3), lack of interpretability (Section 4.4), and constraint satisfaction (Section 4.5).

⁵<http://tinyurl.com/parti-prompts>

4.1 Misinformation

As the quality of generated data synthesized using large-scale generative models increases, it can become increasingly hard to distinguish between real and generated samples, especially for uninformed consumers [53]. Consequently, this can enable the spread of misinformation (e.g., by deep-fakes [69]). To ensure the trustworthiness of information, we need algorithmic solutions that are on par with the advances in generative models and allow us to robustly detect and mark synthetic data. One common approach to the detection of synthetic text and image data is watermarking, where the goal is to manipulate the generated sample, (ideally) with minimal effects on sample quality, with the ability to detect the injected watermark in downstream tasks. There have been several approaches to watermark synthetic data generated using LLMs [97] and diffusion models [247, 223]. However, current watermarking methods are far from perfect [170]. Moreover, it is unclear if the effects of watermarking can be reduced by downstream transformations (like paraphrasing or image manipulation) and to what extent. Therefore, designing efficient frameworks for detecting synthetic data can be an interesting direction for further work.

4.2 Privacy and Copyright Infringement

Interestingly, recent works show that publicly available LLMs and large-scale text-to-image models can implicitly “memorize” training data, in the sense that points from the dataset can be (almost exactly) reconstructed, which potentially infringes on data privacy [23, 22, 188, 136]. This connects to the open question of whether it is possible to train generative models while preserving data privacy. To alleviate this problem, approaches like training generative models with differential privacy (DP) constraints offer an attractive theoretical framework to ensure privacy [111, 41]. However, DP-based approaches suffer from a tradeoff between privacy and utility. Moreover, in the context of image generation, scaling such approaches to high-resolution datasets remains elusive. Therefore, building privacy constraints in large-scale training of generative models can be a promising direction for further research.

In addition to privacy, recent advances in large-scale generative modeling can lead to unauthorized distribution or replication of training data resulting in copyright infringement liabilities⁶. While some recent work tries to alleviate this issue [113, 248], there are several outstanding technical challenges ranging from mitigating copyright infringements during dataset curation [24] to reliable detection of copyright violations in generated samples.

4.3 Fairness

Large-scale generative models are often trained on massive datasets containing billions of samples scraped from the internet. While preprocessing such large datasets often involves tagging or removing toxic content, a variety of other societal biases are often harder to detect. Consequently, the trained models can reflect biases and produce outputs that may be deemed toxic or harmful. For instance, Weidinger et al. [222] outline a series of harms that may result from the use of LLMs that produce discriminatory or exclusionary language, e.g., by amplifying stereotypes. Similarly, multi-modal models may exhibit biases about gender, ethnicity, and religion, among others [82]. While numerous approaches have been proposed to mitigate such biases in a post-hoc manner [6, 56], the achieved changes are often merely superficial [57], leaving the possibility of remnant biases. Further research is necessary to train models that can readily account for multiple forms of fairness with regard to diverse criteria. More importantly, we also need robust and interpretable evaluation metrics to quantify different forms of biases that can adapt to closed-source generative models [245, 197, 104].

4.4 Interpretability and Transparency

Developing reliable methods of evaluating interpretability in DGMs is of crucial importance [169, 84]. In particular, while scaling up large generative models has been shown to improve performance and sample efficiency, their highly complex architecture gives rise to unpredictable effects [220, 177] and demonstrates capabilities that have not been anticipated by model developers. Their lack of transparency and interpretability raises concerns in critical applications such as healthcare [27] or

⁶<https://www.nytimes.com/2023/12/27/business/media/new-york-times-open-ai-microsoft-lawsuit.html>

finance, where understanding model decisions may be crucial for building trust and ensuring safety. Transparency in how the model works is essential to building trust. For example, while LLMs seem to be able to explain their outputs, their explanations are highly unreliable [207]. Research has also questioned the use of attention patterns as reliable explanations [80, 226, 180], potentially due to the heavy use of residual architectures in modern transformers.

An important open question for future research is how and why emergent abilities occur in large language and vision models (or whether the seemingly emergent behavior is due to the selection of metrics as suggested by Schaeffer et al. [177]). The fundamental challenge here is to develop explanation methods that are both well-understood by humans and faithful to the underlying model behaviors. For the former, apart from core developments in ML methods, more scientific methods for user studies and human evaluations can be borrowed from research on user experience design and human-computer interaction [115, 217, 154]. For the latter, efforts should be made to further develop and robustify explainable methods such as counterfactual explanations [214, 186].

4.5 Uncertainty Estimation and Constraint Satisfaction

Language models and other generative models of symbolic sequences have a long history that can be traced back to early studies on prediction probabilities for written language, such as those by Shannon [181]. Their traditional next-token likelihood objective emphasizes just plausibility [91]. However, recent services such as ChatGPT, as well as the models deployed in large commercial search engines, are increasingly expected to serve as universal question-answering engines. With this comes an increasing need for models that produce statements that may be deemed factually accurate and trustworthy while avoiding confabulation, often also referred to as *hallucinations* [91]. Encouragingly, recent studies show that models often do possess the ability to assess the truthfulness of their own statements [89]. Additional evidence can be brought in from external knowledge sources [143]. Another potential direction might be to emphasize probabilistic consistency [47], e.g., between a statement and its negation. This indicates that significant improvements can still be achieved in estimating uncertainty.

Generative models such as ChatGPT are used by millions of people and deployed across diverse use cases. For many of these, they are expected to satisfy additional constraints. In some cases, these merely stem from a desire to have a more controlled form of generation, such as when a generated image is conditioned on a given depth map [242]. In other cases, ethical and societal considerations are key concerns. For instance, widespread calls exist for generative models to avoid toxicity and adopt bias mitigation mechanisms [222]. Current models are also expected to avoid outputs that may lead to harmful effects, for instance, by refraining from responding in ways that could pose a risk to the mental health of human interlocutors and by refusing to carry out tasks related to illegal activities. Currently, this is often achieved using reinforcement learning from human feedback [141], but further research is necessary to mitigate the risk of such constraints being circumvented [183].

Thus, new frameworks that combine uncertainty estimation and constraint satisfaction have the potential to yield AI models that better adhere to our human expectations.

5 Conclusion

Despite recent excitement and hype around the advancements in generative AI, learning a *perfect* generative model is far from its realization. To this end, we identify several core challenges with the current generative modeling frameworks from the lens of adaptability across different domains, efficient resource utilization, and reliable and safe deployment. We believe solving or alleviating these challenges to a large extent, coupled with recent advances in scaling, can unlock the true potential of generative models with major technological and societal implications.

We identified generalization and robustness as major hurdles, demanding methods to handle unseen data and adversarial attacks. Moreover, hidden assumptions regarding data independence and limited representational power necessitate the exploration of more expressive models and the incorporation of prior knowledge, especially in data-scarce scenarios. Moving beyond mere correlation, integrating causal reasoning into DGMs holds promise for enhanced interpretability and robustness. We also emphasized the escalating computational demands and associated barriers to the widespread adoption of DGMs. Efficiencies in training and inference pose key challenges, urging the exploration

of alternative network architectures and low-bitrate model quantization. Subjective evaluation metrics for generated content, such as FID and n-gram matching, present limitations, prompting the search for robust, domain-agnostic alternatives.

We also addressed the challenges and considerations surrounding the responsible deployment of large-scale generative models, pointing to the rising concerns related to misinformation, unintended harm, and lack of trustworthiness. Challenges include combating misinformation, ensuring privacy in data curation, addressing fairness issues, enhancing interpretability, and estimating uncertainty while satisfying ethical constraints.

By confronting the limitations explored, we can transform DGMs from data replicators to transformative tools across various domains. Imagine, for instance, AI agents in healthcare seamlessly integrating diverse medical data to uncover causal relationships, empowering personalized medicine, and accelerating drug discovery. We hope that our paper will point to directions that ultimately contribute to these goals.

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