Generative AI at the PHY Layer

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Abstract

Generative Artificial Intelligence (GAI) has experienced an explosion in popularity in recent years, with many applications still being discovered. Driven by these advances, the use of GAI in Physical Layer applications has been heavily researched. We discuss three such applications, including Semantic Communication, Channel Estimation and Sensing, and Security and provide an overview of the literature in each respective area. Recommended approaches and challenges are presented in addition to a general introduction of each topic. Finally, some challenges facing widespread adoption of GAI technologies are discussed.

Keywords: Generative AI, Wireless Networking, Wireless Communications, Semantic Communications, Encoding, Decoding, Channel Estimation, Channel Sensing, Wireless Security, Mobile Security

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1 aEf Introduction

Recent advances in generative artificial intelligence (GAI) have led to widespread adoption of the technology, aimed at addressing problems in diverse fields. GAI has been heavily researched for its applications to the fields of networking and security. GAI technologies have proven useful in mobile and wireless networking, addressing problems such as network routing, channel estimation, and anomaly detection [Thai-Hoc2024]. This work focuses on GAI networking applications at the physical (PHY) layer.

Section 2 provides brief historical context and a general overview of GAI technologies. Sections 3, 4, and 5 describe the application of GAI to the problems of semantic communication, channel estimation, and network security, respectively. Section 6 provides a summary of the topics discussed.

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2 aEf Generative Artificial Intelligence

GAI has undergone a boom in growth in the last several years fueled by developments in model architecture and training. While traditional artificial intelligence (AI) technologies focus on pattern recognition problems, GAI models have the ability to produce new content including text, imagery, video, and audio. Much of GAI's success has been due to the probabilistic nature of the outputs in contrast to the classically deterministic outputs of traditional AI models. Recent advancements in GAI have been fueled by notable releases from AI research organizations, such as OpenAI (ChatGPT) [OpenAI2024] and Google DeepMind (DeepDream) [Google2024]. As understanding and adoption have grown, these technologies have found widespread application in a variety of industries and research areas, including networking and security [Thai-Hoc2024], [Khoramnejad2024].

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3 aEf Semmantic Communications

Semantic communication (SemCom) broadly refers to the communication and interpretation of meaning instead of the exact communication or reproduction of source data [Liang2024]. More simply, "SemCom focuses on conveying the meaning of the information being transmitted, rather than just the exact data bits" [Khoramnejad2024]. SemCom has the potential to increase spectrum utilization by exploiting redundancy in transmitted data by compressing it to communicate only its essential meaning [Khoramnejad2024], [Liang2024]. A key challenge in SemCom is the design of semantic encoders and decoders [Khoramnejad2024]. In [Grassucci2024], semantic communication is described using the Shannon-Weaver communication model paradigm in which three levels of communication are described (Figure 1). Semantic communication addresses the semantic level of communication, which describes the way that meaning is conveyed [Shannon1949].

3.1 aEf Semantic Encoding

As described by [Liang2024], a semantic encoder leverages background knowledge and context to extract bits containing the core meaning of the transmission. Grassucci, et al. [Grassucci2024] describe a practical approach to the semantic encoding problem, leveraging the strengths of various GAI models for encoding and decoding tasks. In that work, the PHY layer encoder is described as a semantic extractor and the use of Variation Auto Encoders (VAE) models for the semantic extraction task is proposed. VAEs have been used in dimensionality reduction techniques, where they encode the mean and variance of the data into a lower-dimensional Gaussian distribution [Kingma2013]. This lower-dimension latent vector represents the limited information required to reconstruct the complete data.

3.2 aEf Semantic Decoding

In semantic decoding, the decoder inverts the encoding process and recovers the core meaning of the transmission [Khoramnejad2024]. In [Grassucci2024], diffusion models are proposed as a suitable model for the semantic decoding task. During the training of Denoising Diffusion Probabilistic Models (DDPMs), data is transformed into pure noise. The model learns to estimate the amount of noise added to the input and can then reverse the process at decoding time. DDPMs have recently been shown to excel at the semantic decoding task [Khoramnejad2024], [Grassucci2023].

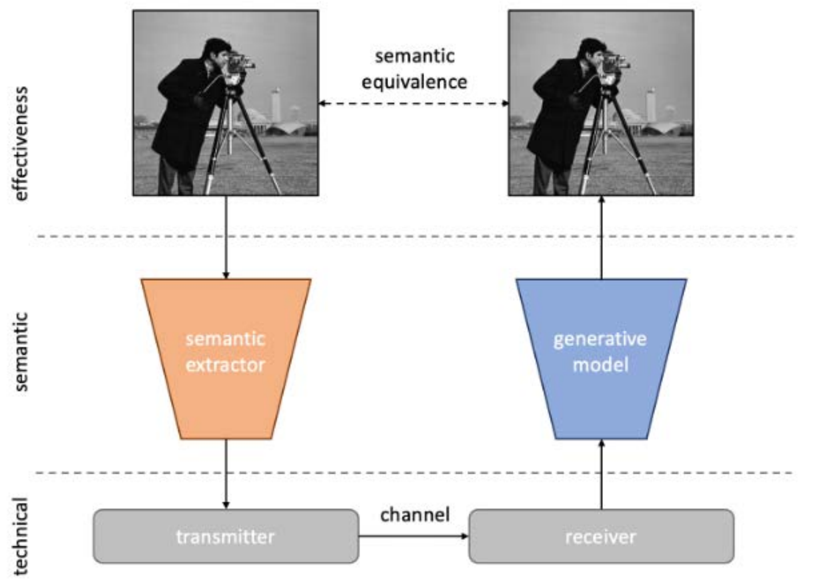

Figure 1: A schematic depicting GAI at the semantic level of the Shannon-Weaver communication model *(reproduced from [Grassucci2024])*.

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4 aEf Channel Estimation and Sensing

GAI has also recently grown in popularity for its use in channel estimation and channel sensing tasks. Channel estimation refers to the problem of detecting the characteristics of the communication channel while channel sensing refers to the problem of determining if a communication channel is available. Historically, channel estimation methods have required the use of sophisticated statistical approaches, like maximum-likelihood estimation [VanHuynh2024], while channel sensing has used approaches, like spectrum sensing, which can be vulnerable to noisy channels [Axell2012].

4.1 aEf Channel Estimation

Channel estimation characteristics can include values such as modulation scheme, signal classification, and beamforming parameters [VanHuynh2024]. Traditional estimation of these characteristics required knowledge of the channel. In [VanHuynh2024], the authors argue that traditional methods of channel estimation will lose performance in increasingly complex wireless systems. In GAI-enabled channel estimation, deep learning (DL) methods are used to learn relationships between channel inputs and outputs. In [Sun2020] and [Ye2020], Generative Adversarial Networks (GANs) are effectively used to retrieve maximum-likelihood estimates of transmitted sequences and model unknown networks. Traditional DL methods are used in [Tang2018] to classify signals by using GANs to augment a training dataset with features learned from the original data.

4.2 aEf Channel Sensing

The use of GAIs in channel sensing seeks to unify the functions of wireless communication and sensing in an approach called Integrated Sensing and Communications (ISAC) [Khoramnejad2024]. As a key technology for 6G, ISAC GAI models analyze the propagation and scattering of transmitted radio waves, adapting to variations in environment and resource allocation [Khoramnejad2024], [Wang2024]. In [Sha2024], VAEs are used for traffic flow modeling and real-time decision-making to adapt to changing urban environments. Similarly, in [Wang2024], coupled diffusion models to generate network graphs and secure communications by abstracting the channel state information (CSI).

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5 aEf Security

Traditional AI techniques fall short in wireless and mobile security applications due to their limited ability to adapt to the rapidly changing cybersecurity threat landscape [Zhao2024]. The use of GAI at the Physical layer provides the opportunity to exploit their dynamic learning capability to address these challenges. In [Zhao2024], the authors discuss several key security areas in which GAI models excel and provide recommendations based on the strengths of various models. One such area is Joint Source-Channel Coding (JSCC) in which a single code is used in the encoding and decoding steps of transmission over a noisy channel [Thai-Hoc2024].

5.1 aEf Joint Source-Channel Coding

In [Bourtsoulatze2019], the authors demonstrate DL-based JSCC in an image transmission application. Two convolutional neural networks (CNNs) are trained as an autoencoding system representing encoding and decoding functions. Image pixels are then mapped directly to complex-valued channel inputs rather than transforming pixel valued to bit sequences. Figure 2 shows a traditional image transmission system (a) compared to the DL-based JSCC system (b) in [Bourtsoulatze2019]. Similarly, in [Tung2022], the authors propose *DeepJSCC-Q*, using Deep Neural Network (DNN) GAI models to quantize inputs prior to transmission.

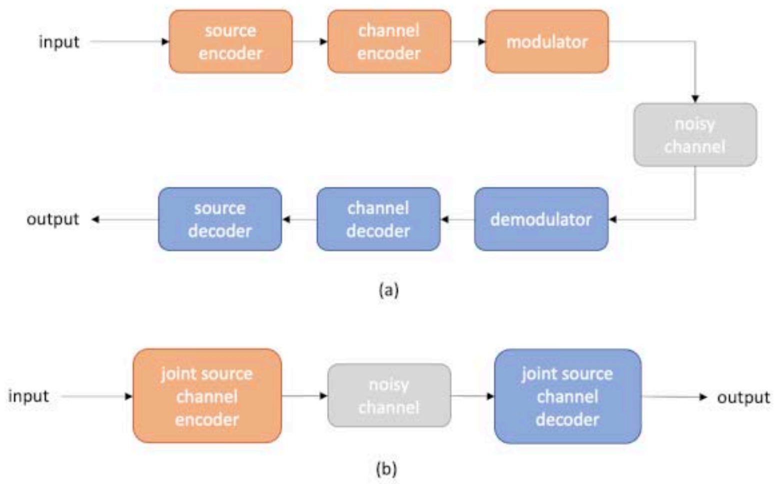

Figure 2: A traditional image transmission model (a) v. a DL-based JSCC model (b) *(reproduced from [Bourtsoulatze2019]).*

In addition to JSCC, many security applications for GAI in the PHY layer exist. Table 1 shows a breakdown of recent literature covering the use of GAIs in PHY layer security. [VanHuynh2024] and [Zhao2024] discuss the strengths of GAI models in threat modeling and anti-jamming applications, recommending GAN and VAE models, respectively. Ultimately, [Zhao2024] shows the robustness of GAN modals in addressing a wide range of security concerns at the PHY Layer.

Table 1. GAI in PHY Layer Security *(reproduced from [Zhao2024]).*

	GAN	**VAE**	**DM**
Confidentiality	• key generation • channel approximation	• transceiver design • JSCC	•
Availability	• jamming detection	•	
Resilience	• spoofing detection	•	
Integrity	• anomaly detection • spectrum sensing • signal reconstruction	• spectrum sensing • signal reconstruction	• noise suppression

Authentication	• RF authentication • channel state authentication	• channel impulse authentication	•

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6 aEf Conclusion

GAI at the PHY layer has been shown to provide many advantages over traditional AI techniques. In many cases GAI models excel because of their ability to adapt to new environmental data and unknown inputs [VanHuynh2024]. In this work, we've discussed the use of GAI in several applications, including SemCom, Channel Sensing, and Security. We've seen how VAEs and DDPMs excel in semantic coding and decoding applications, respectively. Similarly, GANs have been shown to excel in channel sensing and estimation. Finally, GANs, VAEs, and DMs have been shown to have broad application in network security at the PHY layer.

The topics of semantic communication, channel estimation, and security are only three applications among many well-suited for GAI approaches. Other potential tasks include network optimization and resource allocation [VanHuynh2024]. GAI is still a heavily researched area and its uses and capabilities will continue to expan in the future. Further work is required to address the challenges of complexity and scalability associated with GAI techniques and facilitate their wide-spread adoption for PHY layer uses [Thai-Hoc2024].

Acronyms

- GAI: General Artificial Intelligence
- PHY: Physical Layer
- AI: Artificial Intelligence
- SemCom: Semantic Communications
- VAE: Variational Auto Encoder
- DDPM: Denoising Diffusion Probabalistic Model
- DL: Deep Learning
- GAN: Generative Adversarial Network
- ISAC: Integrated Sensing and Communications
- CSI: Channel State Information
- JSCC: Joint Source-Channel Coding
- DNN: Deep Neural Network
- DM: Diffusion Model
- CNN: Convolutional Neural Network

References

[Thai-Hoc2024] Vu, Thai-Hoc, et al. "Applications of Generative AI (GAI) for Mobile and Wireless Networking: A Survey." *arXiv preprint arXiv:2405.20024* (2024)

[OpenAI2024] "Pioneering research on the path to AGI," OpenAI, https://openai.com/research/. Accessed 02 November 2024.

[Google2024] "Research Breakthroughs," Google DeepMind, https://deepmind.google/research/breakthroughs/. Accessed 02 November 2024.

[Khoramnejad2024] Khoramnejad, Fahime, and Ekram Hossain. "Generative AI for the Optimization of Next-Generation Wireless Networks: Basics, State-of-the-Art, and Open Challenges." *arXiv preprint arXiv:2405.17454* (2024).

[Liang2024] Liang, Chengsi, et al. "Generative AI-driven semantic communication networks: Architecture, technologies and applications." *IEEE Transactions on Cognitive Communications and Networking* (2024).

[Grassucci2024] Grassucci, Eleonora, et al. "Generative AI meets semantic communication: Evolution and revolution of communication tasks." *arXiv preprint arXiv:2401.06803* (2024).

[Shannon1949] C. E. Shannon and W. Weaver, "The mathematical theory of communication," 1949.

[Kingma2013] Kingma, Diederik P. "Auto-encoding variational bayes." arXiv preprint arXiv:1312.6114 (2013).

[Grassucci2023] Grassucci, Eleonora, Sergio Barbarossa, and Danilo Comminiello. "Generative semantic communication: Diffusion models beyond bit recovery." *arXiv preprint arXiv:2306.04321* (2023).

[VanHuynh2024] Van Huynh, Nguyen, et al. "Generative AI for physical layer communications: A survey." *IEEE Transactions on Cognitive Communications and Networking* (2024).

[Axell2012] Axell, Erik, et al. "Spectrum sensing for cognitive radio: State-of-the-art and recent advances." *IEEE signal processing magazine 29.3* (2012): 101-116.

[Sun2020] L. Sun, Y. Wang, A. L. Swindlehurst, and X. Tang, "Generative- adversarial-network enabled signal detection for communication systems with unknown channel models," *IEEE Journal on Selected Areas in Communications*, vol. 39, no. 1, pp. 47-60, 2020.

[Ye2020] H. Ye, L. Liang, G. Y. Li, and B.-H. Juang, "Deep learning-based end-to-end wireless communication systems with conditional gans as unknown channels," *IEEE Transactions on Wireless Communications*, vol. 19, no. 5, pp. 3133-3143, 2020.

[Tang2018] B. Tang, Y. Tu, Z. Zhang, and Y. Lin, "Digital signal modulation classification with data augmentation using generative adversarial nets in cognitive radio networks," *IEEE Access*, vol. 6, pp. 15 713-15 722, 2018.

[Wang2024] Wang, Jiacheng, et al. "Generative AI based Secure Wireless Sensing for ISAC Networks." *arXiv preprint arXiv:2408.11398* (2024).

[Sha2024] Sha, Zifan, et al. "Generative AI-Enabled Sensing and Communication Integration for Urban Air Mobility." *2024 IEEE 99th Vehicular Technology Conference (VTC2024-Spring)*. IEEE, 2024.

[Zhao2024] Zhao, Changyuan, et al. "Generative AI for secure physical layer communications: A survey." *IEEE Transactions on Cognitive Communications and Networking* (2024).

[Tung2022] T.-Y. Tung, D. B. Kurka, M. Jankowski, and D. Gu I^ndu I^z, "DeepJSCC- Q: Constellation constrained deep joint source-channel coding," *IEEE J. Sel. Areas Inf. Theory*, vol. 3, no. 4, pp. 720-731, Dec. 2022.

[Bourtsoulatze2019] Bourtsoulatze, Eirina, David Burth Kurka, and Deniz Gunduz. "Deep joint source-channel coding for wireless image transmission." *IEEE Transactions on Cognitive Communications and Networking 5.3* (2019): 567-579.

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