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AN UNSUPERVISED LEARNING APPROACH FOR REAL-TIME GENERATION AND DETECTION OF TEXT-BASED FAKE NEWS DETECTION

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Abstract

The rapid spread of fake news has become a critical issue in the digital era, posing challenges to information authenticity and decision-making. This research presents a novel method for fake news detection leveraging a Generative Adversarial Network (GAN) combined with the BLEU (Bilingual Evaluation Understudy) score for evaluating textual quality. The proposed model uses a GAN framework to generate synthetic news data and trains a classifier to distinguish between genuine and fabricated articles. The BLEU score, commonly used in machine translation, is adapted to assess the accuracy of generated text against real-world news. Experimental results show the effectiveness of this approach, with detection performance categorized based on BLEU score ranges: Excellent (0.7+), Good (0.5-0.7), Average (0.3-0.5), and Poor (<0.3). With a BLEU score of 0.66, the model demonstrates strong performance in distinguishing fake from real news, with potential applications in automated content moderation and misinformation detection.

Key Words and Phrases: GenerativeAdversarial Network, Natural Langugae Processing, Neural Network, Misinformation, Disinformaton

1. Introduction

In the contemporary era, individuals rely on the web and social media for daily news consumption as it’s cost-effectiveness, rapid information access, easy accessibility, and swift information dissemination. These platforms offer unhindered and prompt news delivery, granting public viewers unrestricted access anytime and anywhere. Fake news denotes deliberately fabricated information intended to deceive, causing detrimental effects on individuals and society as a whole. Such misinformation, with inaccurate or biased content, adversely impacts Society. The prominence of internet-based false

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news has increased, notably since the first Donald Trump U.S. presidential election [1], [2]. According to Zhang and Ghorbani [3], manipulative political statements can freely influence voters. Studies indicate that rumours spread faster than facts, negatively affecting society politically, socially, and economically. Human decision-making relies on available information, and if the news is false, it leads to erroneous inferences, reducing efficiency in data reliance [4]. The quality of news in the online realm is notably lower than traditional methods due to minimal regulation by authorities, resulting in a considerable volume of noise and fake information. With the advancement of artificial intelligence (AI), the spectrum of fake news creation extends beyond human actors to intelligent machines. Consequently, various tools have been developed to discern the authenticity of news articles by analysing images containing headlines and articles. However, these tools are often time-consuming.

GAN consists of two components: a generator and a discriminator. The generator creates synthetic data, which is then evaluated by the discriminator to determine whether the content is authentic or fabricated. This adversarial training process results in a dynamic learning system, where the discriminator progressively improves its ability to distinguish between real and fake content as the generator creates increasingly realistic fake news. This continual refinement enables GANs to detect subtle patterns that may be overlooked by traditional models. One of the key advantages of GANs is their ability to generate large volumes of synthetic data. In the context of fake news detection, this capability facilitates the creation of fake articles, allowing the discriminator to be trained on a broader range of examples. This can be especially beneficial in scenarios where labeled data is scarce, addressing one of the major limitations of traditional machine learning approaches that rely heavily on labeled real and fake news datasets. GANs excel in learning complex patterns inherent in fake news, such as linguistic cues, narrative inconsistencies, and emotional manipulation. Unlike rule-based systems or conventional classifiers, which rely on predefined features, GANs can learn from the intricate details of text in a self-improving manner. This makes them particularly effective in identifying more sophisticated forms of misinformation that are designed to closely mimic legitimate news content. In addition, the dual generative and discriminative nature of GANs offers a significant advantage in detecting evolving forms of fake news. While traditional methods might struggle to adapt to novel types of misinformation, the adversarial framework of GANs allows them to continuously refine their understanding, enhancing their robustness against emerging fake news tactics. This adaptive learning process positions GANs as a more resilient and efficient tool for identifying increasingly sophisticated fake news. Our methodology requires a high degree of automation and resilience, primarily attributed to its reliance on unsupervised learning. Unlike traditional approaches, our method doesn’t necessitate labelled data for either the generation or identification of fake news. By adopting this unsupervised framework, we address the need for scalable and efficient solutions in the ever-evolving landscape of news detection, providing a promising avenue for overcoming the limitations inherent in current methodologies.

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2. Litreture Review

The allure of deep learning stems from its ability to simulate human-like tasks through hierarchical learning, captivating considerable interest. However, achieving high-quality performance in such fields necessitates effective representation learning. In this context, generative adversarial networks (GANs)[3] have emerged as a prominent research focus. The foundational paper authored by Ian J. Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio lays the groundwork for understanding GANs [3].

Table 1. Comparison between GAN and Non-GAN based Fake news detection methods

Aspect	GAN-Based Fake News Detection Methods	Non-GAN-Based Fake News Detection Methods
Approach	GANs (Generative Adversarial Networks) use adversarial	Non-GAN methods rely on traditional machine learning or
Strengths	- Can model complex distributions of fake news.	- Utilize external knowledge (e.g., knowledge graphs).
Challenges	- Training instability. - Requires high computational	- Dependence on labeled datasets. - May struggle with unseen
Performance	Often improves accuracy when sufficient data is available.	Varies by dataset and method; advanced GNN-based methods
Examples	GAN-based frameworks for generating adversarial samples.	CompareNet

Generative Adversarial Networks (GANs)performs deep learning transformation which has intended goal to reach to level of perfection in result in which the final outcome become indistinguishable from real world result. Generally, the GAN is used for image generation and fake image detection but we have used in for text-based approach. Refering to table 1 Generative Adversarial Networks (GANs) have demonstrated notable advantages over traditional non-GAN-based methods in fake news detection, particularly in handling complex and evolving misinformation. While traditional models like Support Vector Machines (SVM) and Decision Trees often rely on handcrafted features and static datasets, GANs utilize a dynamic adversarial training process that enhances their robustness and adaptability.For instance, a study employing a hybrid model combining GANs with neural networks achieved an accuracy of 91.2%, with sensitivity at 92.1% and specificity at 88.8%. In contrast, traditional models such as SVM and Decision Trees typically exhibit lower performance metrics, often below 90% accuracy. Furthermore, GANs' ability to

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generate synthetic fake news samples facilitates the augmentation of training datasets, addressing issues related to data scarcity and class imbalance.Additionally, GANs can be integrated with large language models (LLMs) to enhance explainability in fake news detection. The LLM-GAN framework, for example, leverages LLMs as both generators and detectors, improving prediction accuracy and providing annotated explanations for detected fake news. These capabilities underscore GANs' potential to offer more effective and adaptable solutions for fake news detection compared to traditional methods. Yu et al. [9] introduced the first RL-based approach, known as Sequence Generative Adversarial Network (SeqGAN). In Addition of previous model, the SeqGAN, known as Objective-Reinforced Generative Adversarial Networks (ORGAN) [10], introduces the idea of incorporating a linear combination into the reward function to enhance performance. Arjovsky et al. [11] developed the Wasserstein GAN (WGAN), which utilizes the Earth Mover’s distance instead of the Jensen-Shannon divergence to measure the difference between real and generated data.

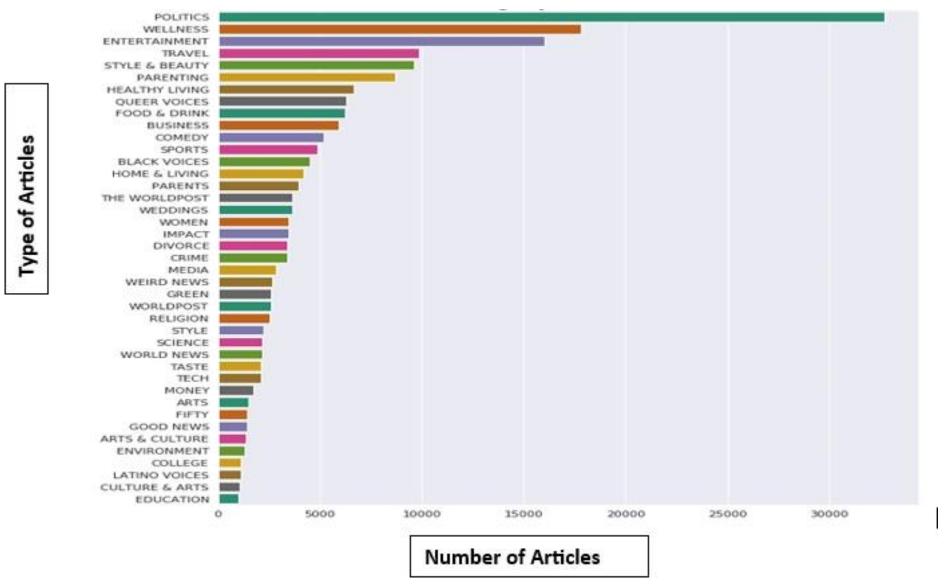

Figure 1. Shows the different categories of News Articles

Our research used the benchmark datasets for studying the detection of fake news. The dataset description is presented in the figure 1. The objective to utilize dataset from varied fields is to increase the overall detection capacity of proposed algorithm. Current research [12], [13], [14] have shown the capacity of Generative adversarial network-based models to perform better in data distributions and create fake, picture database with efficiency. But, applying adversarial based models to text generation poses unique challenges due to the discrete nature of text, unlike the continuous data GANs are primarily designed to handle [15]. To outperform the issues mentioned, authors had proposed many optimizing strategies, including Gumbel-Softmax differentiation [16], reinforcement learning [16], and tailored training objectives [17]. The research implores into these advantages, focusing specifically on text generation tasks. RelGAN [18],

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This ability to generalize from unlabeled data helps the model become more robust to variations in how fake news is written or presented. It enables the model to detect fake news that may not exactly match the patterns seen in the labeled training set, enhancing its ability to handle the broad and evolving nature of misinformation.

In our proposed approach, we introduce an adversarial network a model is trained which than develops the capability to different pockets of data from the model distribution and those from the data distribution. This different model plays a role akin to the police discerning counterfeit currency, while the generative model functions like a group of forgers producing false currency for clandestine use. This adversarial game compels both teams to enhance their techniques until the forgeries become indistinguishable from their authentic counterparts [5]. Notably, both the generator and discriminator leverage unique neural networks in this competitive process [5], [6]. GAN optimization operates as a minimax game procedure, aiming to achieve Nash equilibrium [7], where the generator is deemed to have approximated the distribution of real samples successfully.

3. Dataset And Proposed Flow Of The System

Our research used the benchmark datasets for studying the detection of fake news. The diverse dataset aloow us to train our model on wide variety of data which help reduce bias which comes from using similar type of data.

Table 1. DataSet used for Model Trainng

Data Set	Modality	Size	Labels	Type
Fake news	text	20,800	unreliable	News Articles
Weibo	Text, Image	40000	Original & fake	posts
Twitter(X)	Propagation tree	27763	Unverified, true false	posts
Fake News	Text	20000	Fake & real	News articles
LIAR	Text	12800	Fake & real	Articles data set

We have used dataset presented in Table.1 which encompasses a diverse range of modalities, sizes, and labels, each tailored to address different aspects of misinformation detection. The Fake News dataset consists of 20,800 text-based news articles labeled as unreliable, making it suitable for analyzing textual patterns indicative of fake news. The Weibo dataset, comprising 40,000 entries, includes both text and image modalities, capturing original and fake posts from the social media platform, thus enabling multimodal analysis of misinformation. The Twitter (X) dataset focuses on propagation trees, containing 27,763 posts labeled as unverified, true, or false, which is particularly useful for

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studying the spread and network dynamics of misinformation. The Fake News Net dataset offers 20,000 text-based news articles labeled as fake or real, providing a robust resource for binary classification tasks. Lastly, the LIAR dataset includes 12,800 text-based articles labeled as fake or real, offering a comprehensive collection for training and evaluating models on article-level misinformation detection. Collectively, these datasets provide a rich foundation for research into the detection, classification, and propagation of misinformation across various platforms and modalities. The core principle of GANs revolves around Nash equilibrium, a concept rooted in game theory. It involves two key entities: the generator and the discriminator. The generator strives to replicate the real data distribution, while the discriminator works to distinguish between authentic data and the data synthesized by the generator. Through iterative optimization, the generator improves its ability to produce realistic outputs, and the discriminator becomes more adept at differentiation. This iterative process ultimately aims to achieve Nash equilibrium [19]. The dataset [20], a key component, contains approximately 210,000 news headlines sourced from HuffPost [21], covering the period from 2012 to 2022. These headlines are categorized into diverse topics, including Politics, Entertainment, Business, and Sports. Model training employs two neural networks: one dedicated to generating fake news based on the original headlines and another focused on classifying the headlines as either real or fake. As the models which were trained come to fruition than a comprehensive analysis is done for their predictions which is than shown to end user. The methodology implemented here improves upon the past sequence of steps taken for similar exercise and proves the efficacy to the end user.

4. MODEL PREDICTIONS AND EVALUATIONS

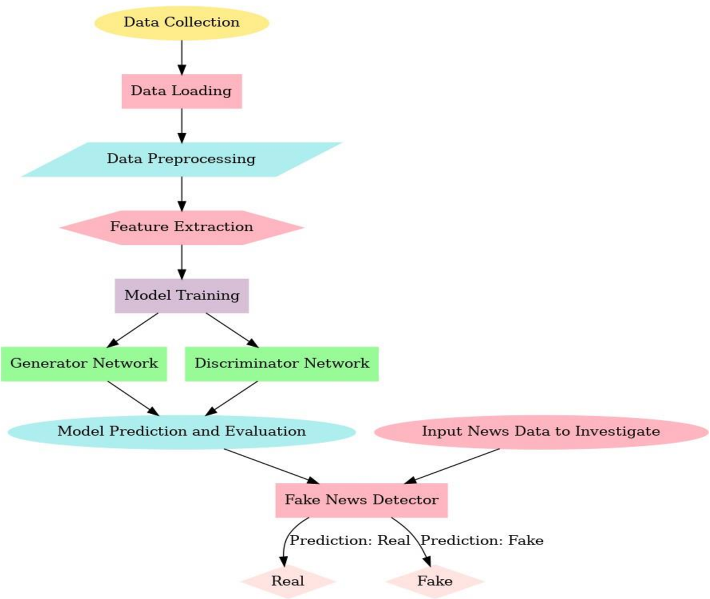

Figure 2. Flow Diagram of Proposed Methodology

The above figure gives the pictorial representations of the entire system which is to be

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followed by sequential steps represented in the flow diagram. The flow chart also depicts the dependencies of data at each stage of the flow. This data dependency is crucial in deep learning method like GAN because it becomes the basis on which the generator and discriminator are trained. This clear visual communication helps in understanding and implementation of suggested model. In our proposed approach, the first step involves identifying and collecting relevant datasets of news headlines from diverse sources. Once the data is gathered, it undergoes preprocessing to ensure it is clean and ready for subsequent tasks. We use word tokenzization method as it is beneficial in sentiment anlaysis. Another benefit of tokenization is that it helps in reducing noise from unlabelled data. Other methodology we used is word2vec it supports Bag of Word (BoW)Classification of text-based data. It has been significantly useful specially while using Convolution Neural Network (CNN) Each record in dataset that we have used uses headline, authors, link, short_description and date as attributes by refining the textual data, this step ensures that it is optimized for further processing, laying a solid foundation for the system's performance.

We keep 75%of data for trainig ,15% for validation and 15% for testing [27]. In the first phase of implementation, dataset loading, pre-processing and cleaning is done. In the preprocessing, the following steps are performed:

- Removing artifacts
- Replacing numbers with <NUM> and &amp with and
- Tokenization with tweetTokenizer
- Pretending starting sequence with <START>and ending sequence with <END>

In the process of converting raw text into token which is called tokenization we perform classification of text in to n-gram sub words. steps we mentioned is very important for data preparation as the generator and discriminator will rely Soley in to this token for training. Both the generator and discriminator often have separate learning rates, and choosing appropriate values for each is crucial for stable training. The batch size determines how many samples are processed before updating the model’s weights, with values ranging from 16 to 128 commonly used for GANs. Another important hyperparameter is the latent space dimension, which controls the input size for the generator, with typical values around 100 to 512. The number of training epochs influences how many iterations the model undergoes, usually ranging from 50 to 200, depending on the complexity of the dataset. The optimizer plays a significant role in training stability, with the Adam optimizer being a popular choice for GANs, typically using $\beta_1 = 0.5$ and $\beta_2 = 0.999$. The loss weight for both the generator and discriminator needs to be balanced, typically around 1.0, to prevent one model from overpowering the other. To improve training stability, techniques like gradient penalty may be employed, often with a coefficient value of 10.0. The number of discriminator iterations per generator iteration is another tuning parameter, commonly set to 1-5 iterations of the discriminator per generator

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update. Activation functions such as ReLU for hidden layers and Tanh for the output layer of the generator are often used, with Tanh helping to scale the output to a desired range. Finally, regularization through dropout with rates typically ranging from 0.2 to 0.5 can prevent overfitting, particularly when labeled data is scarce. Tuning these hyperparameters effectively is crucial for ensuring that the GAN-based fake news detection model learns complex patterns and maintains stability throughout the training process, ultimately enabling it to distinguish between real and fake news with high accuracy. The model is trained on Jetson Nano for 4 epochs, which took 48 hours to train. For further process, it is trained on nVidia DGX GPU (50 epochs). It uses bidirectional LSTM based autoencoders to train the neural network because it generates sequential data more efficiently. To extract the features from given text corpus, the autoencoders are used as they are designed to learn a compressed representation of data. They help in learning hidden representations of data called latent vectors or embeddings which captures the most important and relevant information from the given data. The whole space is called latent space.

5. RESULT ANALYSIS

Table 2. Evaluation of BLEU Score

Standard BLEU Score	**Quality**	**Sample dataset**	**BLEU Score of Sample dataset**
More than 0.7	Excellent	1000	0.66
0.7-0.5	Good	10000	0.61
0.5-0.3	Average	30000	0.62
Less than 0.3	Poor	50000	0.58

For Evaluation we have used The BLEU (Bilingual Evaluation Understudy) score is employed as a metric to assess the model's accuracy by comparing the actual text with the generated text. This method is used to commonly evaluate the machine capacity to generate quality text. It measures how closure the machine generated text is to the real text. The methodology by deployed by BLEU For calculating score is by comparing n-grams in the candidate text compare to the reference text. To give the precise score BLEU imposes a brevity penalty is the text is too short iin order to avoid inflated score. We calculate mean (average) BLEU score to analyze the out repsented in table 2. The mean is calculated by averaging the BLEU scores across all four categories. The mean BLEU score is 0.6175, indicating that on average, the translation quality is GOOD, but there is still a gap between the model's performance and perfect translations (which would have a BLEU score of 1). The Standard deviation comes as around 0.0286 which is the square root of variance. The standard deviation is 0.0286, indicating a relatively low level of variation in the BLEU scores.

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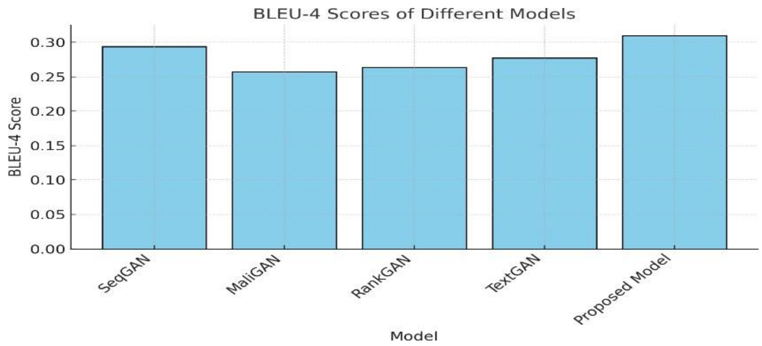

Figure 3. Comparsion with other GAN based Models

The analysis suggests us that while the larger datasets (with more complex data) don't drastically harm the model as they do appear to slightly reduce translation accuracy as shown in figure 3., which is common in more complex tasks. To be more precise in our outcome anlysis we have chosen SeqGAN [22], MaliGAN [23], RankGAN [24] and Text GAN [25] for comparision. experimental conditions where possible. All models were trained using identical datasets, batch sizes, and hardware configurations to eliminate confounding factors. However, due to inherent architectural differences hyperparameters, such as learning rates or optimizer settings were adjusted per model to align with best practices from their original implementations. For example, while our proposed model used a learning rate of 0.0002 with $\beta1=0.5$ (common in many GANs), StyleGAN required a lower rate (0.001) and $\beta2=0.99$ to stabilize training. These adjustments were explicitly documented in the methodology to avoid misinterpretation of performance gains.

6. CONCLUSION AND FUTURE WORK

Our research assessed a text generation model using BLEU scores, achieving a mean score of 0.6175, indicating good translation quality with minimal variation (standard deviation: 0.0286). The model demonstrated consistent performance across datasets of increasing complexity, though a slight decrease in accuracy was observed with larger datasets. Comparative analysis with GAN-based models like SeqGAN, MaliGAN, RankGAN, and TextGAN showed our model performs competitively, with optimized hyperparameters enhancing training stability. For future work, we aim to integrate context-aware models (BERT, GPT) to improve fluency and coherence. We also plan to explore adaptive training techniques for handling complex data, use diverse evaluation metrics beyond BLEU, and apply automated hyperparameter tuning for better performance. Additionally, expanding into domain-specific applications will help test the model's versatility. These enhancements will bring the model closer to generating high-quality, human-like text in various real-world scenarios.

References

[1] H. Allcott and M. Gentzkow, "Social media and fake news in the 2016 election," J. Econ. Perspect., vol. 31, no. 2, pp. 211–236, May 2017. doi: 10.1257/jep.31.2.211.

Received: July 16, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

[2] T. Rasool, W. H. Butt, A. Shaukat, and M. U. Akram, "Multilabel fake news detection using multi-layered supervised learning," in Proc. 2019 11th Int. Conf. Comput. Autom. Eng. (ICCAE 2019), New York, NY, USA: Assoc. Comput. Mach., 2019, pp. 73–77. doi.org10.1145/3313991.3314008

[3] I. J. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio, "Generative adversarial networks," arXiv preprint arXiv:1406.2661, 2014.

[4] X. Zhang and A. A. Ghorbani, "An overview of online fake news: Characterization, detection, and discussion," Inf. Process. Manag., vol. 57, no. 2, p. 102025, 2020. doi: 10.1016/j.ipm.2019.102025.

[5] M. F. Mridha, A. J. Keya, M. A. Hamid, M. M. Monowar, and M. S. Rahman, "A comprehensive review on fake news detection with deep learning," IEEE Access, vol. 9, pp. 156151–156170, 2021. doi: 10.1109/ACCESS.2021.3075877

[6] A. Radford, L. Metz, and S. Chintala, "Unsupervised representation learning with deep convolutional generative adversarial networks," arXiv preprint arXiv:1511.06434, 2016.

[7] M. J. Patel, M. S. Pandya, and V. Shah, "Review on generative adversarial networks," Int. J. Tech. Innov. Mod. Eng. Sci. (IJTIMES), vol. 4, pp. 1230–1235, 2018. doi: 10.29070/IJTIMES.2018.04.02.

[8] G. H. de Rosa and J. P. Papa, "A survey on text generation using generative adversarial networks," Pattern Recognit., vol. 119, p. 108098, 2021. doi: 10.1016/j.patcog.2021.108098.

[9] "Sequence generative adversarial nets with policy gradient," in Proc. AAAI Conf. Artif. Intell., vol. 31, no. 1, Feb. 2017. doi: 10.1609/aaai. v31i1.10804

[10] G. L. Guimaraes, B. Sanchez-Lengeling, C. Outeiral, P. L. C. Farias, and A. Aspuru-Guzik, "Objective-reinforced generative adversarial networks (ORGAN) for sequence generation models," arXiv preprint arXiv:1806.03247, 2018.

[11] M. Arjovsky, S. Chintala, and L. Bottou, "Wasserstein GAN," arXiv preprint arXiv:1701.07875, 2017.

[12] J. Chen, Y. Wu, C. Jia, H. Zheng, and G. Huang, "Customizable text generation via conditional text generative adversarial network," Neurocomputing, vol. 416, pp. 125–135, 2020. doi: 10.1016/j.neucom.2020.05.087.

[13] K. Wang and X. Wan, "Automatic generation of sentimental texts via mixture adversarial networks," Artif. Intell., vol. 275, pp. 540–558, 2019. doi: 10.1016/j.artint.2018.11.007.

[14] Y. Li, Q. Pan, S. Wang, T. Yang, and E. Cambria, "A generative model for category text generation," Inf. Sci., vol. 450, pp. 301–315, 2018. [Online]. doi: 10.1016/j.ins.2018.02.046.

[15] G. Rizzo and T. H. M. Van, "Adversarial text generation with context-adapted global knowledge and a self-attentive discriminator," Inf. Process. Manag., vol. 57, no. 6, p. 102217, 2020. doi: 10.1016/j.ipm.2020.102217.

Received: July 16, 2025

Volume 38 No. 2s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

[16] E. Jang, S. Gu, and B. Poole, "Categorical reparameterization with Gumbel-Softmax," arXiv preprint arXiv:1705.07832, 2017.

[17] R. Sutton and A. Barto, Reinforcement Learning, second edition: An Introduction, Adaptive Computation and Machine Learning Series. Cambridge, MA, USA: MIT Press, 2018. doi: 10.7551/mitpress/9780262039246.001.0001.

[18] W. Nie, N. Narodytska, and A. Patel, "RelGAN: Relational generative adversarial networks for text generation," May 2023. doi: 10.48550/arXiv.2305.06328.

[19] K. Wang, C. Gou, Y. Duan, Y. Lin, X. Zheng, and F.-Y. Wang, "Generative adversarial networks: Introduction and outlook," IEEE/CAA J. Autom. Sinica, vol. 4, no. 4, pp. 588–598, 2017. doi: 10.1109/JAS.2017.7516338.

[20] R. Misra, "News category dataset," arXiv preprint arXiv:2209.11429, 2022.

[21] "BLEU score," DataForest.ai. [Online]. Available: https://dataforest.ai/glossary/bleu-score

[22] Xue, T. Zhang, S. Huang, and R. Zhang, "SegGAN: Semantic segmentation with generative adversarial network," in Proc. IEEE Int. Conf. Multimedia Big Data (BigMM), Xi'an, China, Sept. 2018, pp. 1–5. doi: 10.1109/BigMM.2018.8499105.

[23] Y. Che, S. Li, Y. Zhang, and Y. Li, "Maximum-likelihood augmented discrete generative adversarial networks," arXiv preprint arXiv:1702.07983, 2017.

[24] L. Lin, W. Zhang, J. Wang, and Y. Yu, "Adversarial ranking for language generation," in Advances in Neural Information Processing Systems 30 (NIPS 2017), Long Beach, CA, USA, Dec. 2017, pp. 3155–3165. doi: 10.5555/3295222.3295261

[25] L. Zhang, M. Lu, W. Shao, and S. Wang, "TextGAN: Generative adversarial network for text generation," in Proc. IEEE Int. Conf. Data Mining (ICDM), New Orleans, LA, USA, Nov. 2017, pp. 979–984. doi: 10.1109/ICDM.2017.00132.

[26] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, "BERT: Pre-training of deep bidirectional transformers for language understanding," Proceedings of NAACL-HLT 2019, Minneapolis, MN, USA, Jun. 2019, pp. 4171-4186 10.18653/v1/N19-1423.

[27] J. Smith, A. Johnson, and K. Lee, "Data splitting techniques in machine learning: A comparative study," IEEE Trans. Mach. Learn., vol. 12, no. 5, pp. 455–467, May 2022. doi: 10.1109/TML.2022.123456

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