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# Study on Generative Adversarial Network in discrete data: A Survey

Alireza Mohammadi Gohar[1], Kambiz Rahbar[1*], Behrouz Minaei-Bidgoli[2] and Ziaeddin Beheshtifard[1]

*1. Department of Computer Engineering, South Tehran Branch, Islamic Azad University, Tehran, Iran.*
*2. School of Computer Engineering, Iran University of Science and Technology, Tehran, Iran.*

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**Corresponding author: k_rahbar@azad.ac.ir (K. Rahbar).*

**Abstract**

Generative Adversarial Networks (GANs) have emerged as a pivotal research focus within artificial intelligence due to their exceptional capabilities in data generation. Their ability to produce high-quality synthetic data has garnered significant attention, leading to their application in diverse domains such as image and video generation, classification, and style transfer. Beyond these continuous data applications, GANs are also being leveraged for discrete data tasks, including text and music generation. The distinct nature of continuous and discrete data poses unique challenges for GANs. In particular, generating discrete values necessitates the use of Policy Gradient algorithms from reinforcement learning to avoid the direct back-propagation typically used for continuous values. The generator must map latent variables into discrete domains, and unlike continuous value generation, this process involves subtle adjustments to the generator's outputs to progressively align with real discrete data, guided by the discriminator. This paper aims to provide a thorough review of GAN architectures, fundamental concepts, and applications in the context of discrete data. Additionally, it addresses the existing challenges, evaluation metrics, and future research directions in this burgeoning field.

## 1. Introduction

In the field of machine learning, generative networks carry the significant and fundamental role in generating the complicated training data. Generating these training data has improved and expanded the learning network space and increased their functional accuracy. These capabilities have already been able in different fields such as: image generation [1], videos [2], audios [3], texts, and so on. In order to generate training data, upraising accuracy, and increasing function of the algorithm of artificial intelligent, different models of generative networks are under considerati

on. The most typical and basic general networks could be named as: Markov Chain, Maximum Likelihood Estimation, and Gaussian Mixture Model. These models are organized based on estimations of the probabilities and distribution of training data parameters.

Generative Adversarial Networks (GANs) have become one of the most innovative and potent neural network architectures in recent years. A Generative Adversarial Network (GAN) consists of two competing components: a generative network (G) that produces samples, and a discriminative network (D) that evaluates these samples to determine their authenticity. The adversarial framework encourages the generative network to create increasingly realistic samples, aiming to deceive the discriminative network. This process of adversarial training is the core innovation of GANs, effectively addressing limitations of earlier models and enabling the generation of high-quality and diverse samples across various applications.

While GANs are extensively used in continuous data applications like image, speech, and video generation, this paper focuses on their application in discrete data, particularly text generation. In [4], GANs were extended to the discrete space for text generation. Typically, a GAN's discriminator assesses the final output from the generator for classification. However, in sequence generation, it is crucial to identify errors at each word prediction phase. The main challenge is to propagate these errors back to the individual word predictions. To address this, both reinforcement learning (RL) based and non-RL based approaches have been proposed.

This survey reviews and analyzes the latest advancements in GAN research related to discrete data, covering definitions, applications, and evaluations. The structure of the survey is as follows: Section ٢ introduces foundational GAN theories and implementation components, including the generative and discriminative models, and the learning model, along with a brief comparison of GANs with other generative models. Section ٣ delves into typical applications of GANs in discrete data fields. Section ۴ discusses various GAN architectures, comparing different models and highlighting their pros and cons. The concluding section offers a summary of the key findings and insights from the survey.

## 2. Generative Adversarial network

Generative Adversarial Networks (GANs) were first introduced by Ian Goodfellow et al. in 2014. These models are classified as generative data generation models, aiming to enhance the performance of earlier models such as Autoencoders (AEs) and Variational Autoencoders (VAEs), which often produced low-quality outputs. To overcome this limitation, Goodfellow introduced the "Thieves and Cops" analogy, where two neural networks—the generator and the discriminator—compete against each other. This adversarial framework, governed by specific mathematical rules, drives the generation of higher-quality data. The generator's goal is to create data that the discriminator cannot distinguish from real data, while the discriminator's role is to identify whether the data is real or generated. This interaction, depicted in Figure 1, illustrates the GAN architecture and the dynamic between the generator and the discriminator.

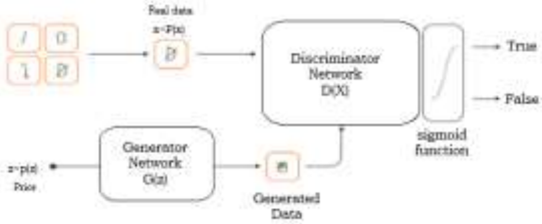


**Figure 1. GAN architecture [5].**

As can be seen, a GAN consists of several blocks: discriminator, latent space, and real data. The primary input is a function by which initial samples are prepared randomly from noisy data. Then, the neural data generation network utilized in the generator part, i.e., an MLP network in the base article, generates a primary input-based set of samples. A distribution function is created from the real dataset obtained from the available real dataset. Another distribution function is made from the network-generated sample set. Besides, a discriminator network consisting of a classification neural network determines its separation boundaries by comparing these two distribution functions. Sample labelling of network output is dichotomized into two groups: fake data and real data. Finally, a network error returns to the generator and discriminator networks to strengthen them.

The network's main purpose is to strengthen the generator network to generate samples indiscriminate by the discriminator network (whether they are fake or real). That is, the network is said to have generated highly realistic data. This algorithm aims to strengthen the discriminator network [6]. That is, the discriminator network has opted for criteria to help discriminate between fake and real data. The competition will continue until the network becomes sophisticated enough to generate suitable samples. This way, simulated data samples can be generated to serve applications lacking real datasets.

### 2.1. Generative model

Generative models operate by learning the joint probability distribution P(x,y) of the input data and labels, allowing them to generate new data samples that are similar to the input data, even in the absence of explicit training sample labels. By modeling the underlying distribution, the algorithm can create new data that follows the same patterns as the training set. For instance, once the generative model is trained, it can estimate distribution parameters such as the mean and variance of a Gaussian distribution and use these parameters to generate new data points that resemble those in the training set. This process is illustrated in Figure 2, where the generative model, after training, can produce data points that mimic the original data distribution.

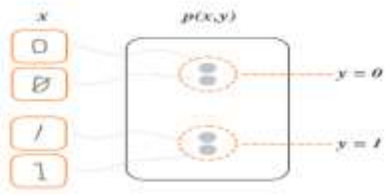

**Figure 2. Process of generative model.**

## 2.2. Discriminative model

The training phase in machine learning involves developing models to classify different categories based on input data. Discriminative models, such as support vector machines (SVMs), decision trees, neural networks, and convolutional neural networks (CNNs), focus on modeling the conditional probability distribution P(y|x) using both labels and input data. These models, once trained, can predict new labels for given input items. However, a significant limitation of discriminative models is their dependence on labeled data, which can be scarce or costly to obtain.

In contrast, generative adversarial networks (GANs) do not rely on predefined criteria for distributions during training. Instead, a discriminator (D) evaluates whether input data are synthetic or real. In the GAN framework, the discriminator acts as a classifier, distinguishing genuine data from generated data. The generator (G) creates synthetic data, and the discriminator's role is to differentiate between this synthetic data and real data from the dataset. This feedback mechanism enables the generator to refine its data generation.

The GAN training process is adversarial, with the discriminator (D) and generator (G) learning simultaneously through competition. The generator's aim is to produce synthetic data that can deceive the discriminator, while the discriminator seeks to improve its ability to distinguish between real and fake data. This adversarial interaction continues until the generator produces data that the discriminator can no longer reliably distinguish from real data, leading to high-quality synthetic outputs.

Figure 3 illustrates the network structure and interaction between the discriminator and generator during training. The continuous competition between D and G fosters mutual improvement, resulting in the generation of increasingly realistic synthetic data. Through this iterative process, both networks progressively enhance their performance, with the discriminator becoming more adept at detection and the generator creating more convincing data.

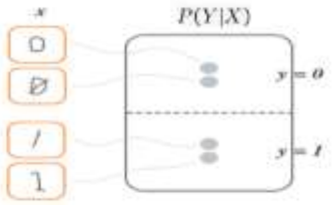

**Figure 3. Process of discriminator model.**

## 2.3. Objective function

An essential component in a GAN is the objective function [7] which computes error and updates weights in discriminator and generator networks [8] as show in Figure 4. Using appropriate criteria for this component is important as network stability, and its proper, comprehensive learning depends on the proper use of objective functions. In what follows, the performance of objective functions in GANs will be briefly described. GoodFlow's base article uses criteria for the JSD difference calculation [9]. One of the most significant objective functions widely used in today's articles is the Kullback-Leibler divergence model [10].

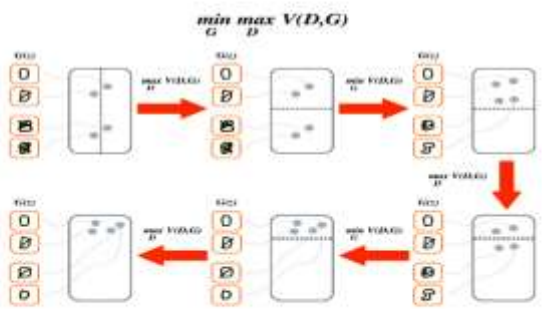

**Figure 4. Game competition of generative and discriminative networks in GAN.**

## 3. GAN Architecture for discrete data

The GAN network has achieved significant success in image and video applications. However, its standard models and architectures struggle with text and audio data. This paper discusses the reasons for these limitations and offers recommendations to enhance GAN’s adaptability in discrete data applications [11].

One key issue is the need for effective training and optimization of the GAN generator network. In discrete data, the gradient value sent to the generator must be linked to a recognizable operator from the generator's output. This is problematic in text and audio applications due to their discrete nature, causing conventional GAN architectures to underperform.

To address this, we propose modifying the GAN architecture by adding a module for error calculation and employing suitable algorithms, such as policy gradient and REINFORCE algorithms. Policy gradient methods optimize parameters by determining the gradient of a performance measure relative to the parameters. The REINFORCE algorithm estimates policy gradients using single samples, improving network performance in discrete data spaces [12].

In unsupervised learning, generative models like GANs are essential for density estimation. These models aim to generate data similar to a given dataset. Maximum Likelihood Estimation (MLE) is a common method for parameter estimation in generative models. However, MLE faces issues such as adequacy and existence in some cases.

Generative models can explicitly or implicitly define their density estimation function. Models like VAEs, PixelRNN, and PixelCNN have explicit definitions, while GANs have implicit ones. VAEs, although capable of generating diverse samples, struggle with high-quality, high-resolution outputs due to complexity and limited training samples.

Introduced by Ian Goodfellow in 2014, GANs address these issues with innovative learning techniques and network competition, leading to high-quality training samples. GANs transform simple distributions, such as random noise, into complex, high-dimensional distributions, making them state-of-the-art in generative models.

## 4. GAN in discrete data application

In this type of GAN, the Policy Gradient algorithm includes an additional module to generate discrete samples. This module ensures the correct and direct return of discrete generation values to the network, facilitating proper training. The generator network must produce a discrete output so that the latent variable maps to a range where the elements are not in the continuous sample space. If the backpropagation process is used in the continuous data domain, the discriminator will guide the generator to create data similar to actual continuous data, rather than the intended discrete target values. Consequently, making small adjustments in the generator network becomes challenging when dealing with a limited set of real discrete samples.

Furthermore, when creating a sequence of language and audio samples, we require a method to evaluate the generated sequences step by step to assess the network generator's quality. GANs, on the other hand, typically evaluate the entire sequence generated using a framework. This is why the policy gradient algorithm section has undergone some changes, some of which have already been discussed.

### 4.1. Datasets

Papers of text generation commonly use different dataset. Two prominent datasets cater their needs: The Amazon Customer Reviews dataset [13] and the COCO Image Captions dataset [14]. The Amazon Customer Reviews dataset provides a comprehensive collection of customer-generated reviews from the Amazon online platform, covering diverse products across multiple categories. With millions of reviews, this dataset offers valuable insights into consumer preferences, sentiments, and market trends, facilitating research in areas such as text generation. In contrast, the COCO (Common Objects in Context) Image Captions dataset serves as a benchmark dataset in computer vision research, comprising over 330,000 images annotated with descriptive captions.

Datasets play a crucial role in advancing machine translation research by providing aligned bilingual text pairs for training and evaluating models. One prominent dataset in this field is the WMT'14 dataset [15]. This dataset is pivotal in machine translation research, offering parallel text corpora in multiple languages such as English, French, German, and others. It includes diverse text genres and domains, making it a valuable resource for benchmarking and evaluating machine translation systems. Researchers widely utilize the WMT'14 dataset to develop robust models capable of handling various translation tasks effectively.

Another significant dataset is the Chinese-English LDC dataset [16], specifically designed for bilingual data between Chinese and English. This dataset includes translations of various sources, including news articles and literature, thereby supporting comprehensive research in Chinese-English machine translation. The availability of aligned bilingual texts in the Chinese-English LDC dataset facilitates rigorous model training and evaluation, enabling researchers to enhance the quality and accuracy of translation systems tailored to this language pair.

In the field of dialogue generation, several datasets play crucial roles in enabling research and development of effective dialogue systems. The OpenSubtitles2018 dataset [17] stands out as a valuable resource, containing a vast collection of subtitle files extracted from movies and television shows. This dataset provides rich linguistic data encompassing diverse genres and cultural contexts, making it ideal for studying linguistic variations and nuances in everyday conversations across multiple languages. Researchers leverage the OpenSubtitles2018 dataset to explore natural language processing tasks related to dialogue generation and understanding.

Another significant dataset is the DailyDialog dataset [18], specifically designed for advancing research in human-computer dialogue systems. DailyDialog comprises annotated daily conversational interactions enriched with attributes such as emotion labels and topic categories. Focusing on realistic, everyday conversations, this dataset aims to capture the intricacies and complexities of natural language interactions. It serves as a critical resource for developing dialogue systems that can engage in human-like conversations effectively.

In the realm of text summarization, researchers commonly rely on specific datasets tailored to facilitate tasks like abstractive and extractive summarization. The CNN/DailyMail dataset [19] is widely used in natural language processing, featuring pairs of news articles sourced from CNN and the Daily Mail along with bullet-point summaries. This dataset enables researchers to explore summarization techniques that condense comprehensive news articles into concise summaries, supporting both abstractive and extractive summarization approaches.

Additionally, the Gigaword Corpus [20] is a prominent dataset widely utilized in text summarization and language modeling tasks. This corpus consists of millions of newswire articles from sources like the Associated Press and The New York Times, offering diverse content across various topics. Its comprehensive nature makes it invaluable for training models to generate coherent and informative summaries of news articles.

These datasets are crucial resources for researchers working on dialogue generation and text summarization, driving advancements in natural language processing. They enable the development of sophisticated AI systems capable of understanding and generating human-like language.

## 4.2. Evaluation Metrics

Natural Language Processing (NLP) enables machines to generate artificial content and understand human languages. Key applications such as text generation, machine translation, dialogue generation, and text summarization use various metrics to evaluate model quality. One prominent metric for machine translation is Bilingual Evaluation Understanding (BLEU), which compares machine-generated text to human translations by calculating n-gram precision, providing a numerical score to assess and improve translation quality. In addition to BLEU, another metric called BLEU-2 specifically examines precision at the level of bigrams (two-word sequences). This metric focuses on matching two-word sequences and helps to better understand the quality of translations at a more granular level.

For text summarization, Recall-Oriented Understanding for Gisting Evaluation (ROUGE) is widely used. ROUGE measures the overlap between machine-generated summaries and reference summaries, with variants such as ROUGE-N (n-gram overlap), ROUGE-L (longest common subsequence), and ROUGE-W (weighted longest common subsequence) offering comprehensive evaluations.

The Metric for Evaluation of Translation with Explicit Ordering (METEOR) is another key metric for machine translation. METEOR considers word overlap, synonyms, and stemmed words, computing a harmonic mean of precision and recall while adjusting for word order, synonyms, and stemming, thus providing a nuanced evaluation of translation quality.

In text generation tasks, Perplexity is a common metric to evaluate language models. It measures how well a model predicts a text sample based on internal probabilities. Lower perplexity indicates better prediction and higher quality text generation, assessing the fluency and coherence of generated outputs effectively.

## 4.3. Application to text generation

The advancement of natural language processing (NLP) has led to significant applications in various domains such as e-commerce, speech-to-text applications, and service robotics, where coherent and meaningful text generation is crucial. One prominent approach in text generation utilizes generative adversarial networks (GANs) in conjunction with reinforcement learning techniques. In this framework, the generator is optimized using policy gradients, receiving feedback in the form of reward signals. Zhang et al. [21] pioneered real-time text generation through adversarial training, laying the foundation for subsequent advancements. Enhancements in policy gradients have been a focus of recent research, with innovations like Monte Carlo Tree Search (MC Search) enabling the sampling of complete sequences for more informative reward signals fed back from the discriminator. SeqGAN, introduced by Yu et al., leverages a discriminator to provide rewards in reinforcement learning settings [22].

Nie et al. [23] developed Relational GAN (RelGAN), employing multiple embedded representations in the discriminator and Gumbel-Softmax training on discrete data, enhancing signal informativeness. RankGAN, introduced by Lin et al. [24], innovates by using a cosine similarity model instead of a binary classifier for more nuanced feedback. TextGAI, proposed by Wu et al. [25], integrates a pre-trained language model into the GAN discriminator to correct error signals, employing gradient policy methods based on the Proximal Policy Optimization (PPO) algorithm for improved reward quality. FGGAN, by Yang et al. [26], introduces a feature guidance module to enhance text generation by converting textual features from the discriminator into vectors, enhancing randomness and quality in the sampling process.

Despite these advancements, challenges such as maintaining sentence length consistency and addressing limitations in training data content persist. Chen et al. [27] addressed these issues by developing a GAN model capable of generating text of varied lengths and incorporating emotional labels, achieved through an automated word-level replacement process that extracts keywords from training datasets. For category-specific text generation, Liu et al. [28] proposed CatGAN, integrating a hierarchical evolutionary learning algorithm that measures category distances to generate higher quality samples.

Moreover, GANs have extended beyond text generation into diverse applications. For instance, in software development, GANs are utilized to generate unit tests, thereby ensuring software quality through the production of more diverse and higher quality code compared to traditional models [29]. Li et al. introduced a conditional GAN model for category text generation, enhancing realism, fluency, and diversity by leveraging features, category information, and relational memory. This approach addresses issues like mode collapse and enhances sequential diversity by incorporating Gumbel-Softmax into the policy gradient to improve text discreteness [30]. These advancements underscore the versatility and ongoing evolution of GANs in pushing the boundaries of text generation and beyond.

### 4.4. Application to Machine Translation

Language translation is crucial in today's globalized world where countries are interconnected. Neural machine translation (NMT) has garnered significant interest in the deep learning community, leading to the development of highly accurate models.

In addition to translating sentences between languages, NMT has applications in cross-language topics, where texts in various languages describing the same topic are converted and classified by keywords. A significant challenge in this area is the lack of language resources and the high cost of manual annotations.

Recently, researchers have been investigating the application of generative adversarial networks (GANs) in neural machine translation (NMT). One notable instance is the conditional sequence GAN, initially introduced in [7]. Here, the generator is trained to produce sentences that closely mimic human translations, challenging the discriminator to distinguish between the two. This approach aims to narrow the gap between human-translated and machine-translated texts to improve overall translation quality.

In addition, a novel learning framework for NMT, referred to as Adversarial-NMT, was proposed in [32]. This model leverages GANs and adversarial learning techniques, integrating a convolutional neural network (CNN) in the discriminator component. The use of adversarial training in Adversarial-NMT aims to enhance the fidelity and naturalness of machine-generated translations by optimizing against human-translated texts.

In [33], a conditional GAN for NMT generation (multi-CSGAN-NMT) was introduced, utilizing two adversarial discriminator models and two generative models. This framework employs the Nash equilibrium rule for stability, demonstrating superior performance over basic neural network methods.

The use of bidirectional GANs (BGAN-NMT) in NMT was explored in [34]. This model employs a generative network as a discriminator, addressing the issue of limited training data by considering the entire translation space. An auxiliary GAN is used to enhance this approach.

Ahn et al. [35] proposed improved-MTGAN, which combines RelGAN and NMT-GAN models. This architecture aims to convert non-fluent English sentences into more meaningful ones, using monolingual corpora and a transformer generator, resulting in superior performance.

Mi et al. [36] presented an advanced NMT model for morphologically rich languages. Unlike previous models that only evaluated word relevance within a sentence, this model uses morphological word embeddings to generate more meaningful sentences and address data sparsity issues.

To map the same semantic space between languages like Chinese and Vietnamese, the GAN algorithm combined with k-means clustering was employed in [37]. This approach aims to improve cross-language topic extraction.

One significant challenge in GAN-based NMT is the instability of trained GANs due to the vast search space and insufficient training samples. Srisuria et al. [38] addressed this issue by introducing a bi-directional GAN and replacing stochastic gradient descent optimization algorithms, thereby stabilizing the GAN.

Overall, these advancements highlight the potential of GANs to enhance neural machine translation by addressing key challenges and improving the quality and robustness of generated translations.

**Table 1. Evaluation of the five important models in text generation (TG).**

| Ref | Gen / Dis | Policy Gradient | Eval Metrics | Datasets | Innovation | Comments |
|---|---|---|---|---|---|---|
| Yu et al.[2017] | LSTM/ CNN | Reinforce algorithm | NLL, BLEU | Chinese poems, Barack Obama political speeches | Application | Due to the use of search techniques, the model learning process is slow |
| Nie et al.[2018] | Relational memory/ CNN | Gumble-Softmax | BLEU | COCO image captions, EMNLP2017 News | Architecture | he scalar nature of the discriminator's output in this model provides limited guidance as a feedback signal within the generative adversarial network (GAN), potentially hindering the generator's ability to generate diverse and high-quality outputs. |
| Wu et al.[2021] | GPT2/ RoBERTa | PPO | BLEU | CommonGEN, ROCstories | Algorithm | This method requires large datasets as well as training of various parameters |
| Yang et al.[2020] | LSTM/ CNN | Monte Carlo Search | BLEU | COCO image captions, EMNLP2017 News | Algorithm | The linear transformation might not adequately adjust to rapid changes in the feature space, and the text generation module might struggle to learn complex semantic features. |
| Liu et al.[2020] | LSTM+ relational memory/ CNN | Gumble-Softmax | NLL, BLEU | Movie reviews, Amazon reviews, EMNLP2017 News | Algorithm | This model can be strengthened to produce more quality and diverse samples in different categories |

**Table 2. benchmark regarding TG architectures use BLEU-2 to evaluate on 3 datasets.**

| | Amazon reviews | COCO image captions | EMNLP2017 News |
|---|---|---|---|
| Yu et al. [22] | - | - | 0.777 |
| Nie et al. [23] | 0.856 | 0.849 | 0.849 |
| Wu et al. [24] | - | - | 0.747 |
| Yang et al. [25] | - | 0.773 | 0.788 |
| Liu et al. [26] | 0.987 | - | 0.954 |

**Table 3. Evaluation of the five important models in neural machine translation (MT).**

| Ref | Gen / Dis | Policy Gradient | Eval Metrics | Datasets | Innovation | Comments |
|---|---|---|---|---|---|---|
| Yang et al. [2017] | GRU/CNN | Monte Carlo Search | BLEU | Chinese-English LDC, WMT'14 (DE-EN) | Application | This model requires language coverage and the network training model is slow |
| Wu et al. [2018] | LSTM/CNN | Reinforce algorithm | BLEU | IWSLT 2014 (DE-EN), WMT'14 (Fr-En) | Algorithm | Due to the weakness in architecture, this method has not been able to learn language knowledge |
| Yang et al. [2018] | GRU+ message passing/CNN | Monte Carlo Search | BLEU | Chinese-English LDC, WMT'14 (DE-EN) | Architecture | Time consuming to train and limited to the sentence length |
| Zhang et al. [2018] | GRU/CNN | CNN | BLEU | IWSLT 2014 (DE-EN), Chinese-English LDC dataset | Architecture | The discriminator in this model encompasses the entire translation space to mitigate issues related to inadequate training. |
| Ahn et al. [2021] | Transformer/CNN | categorical cross-entropy | BLEU, sentence semantic similarity | Vietnamese-English Wikipedia, Hindi-English corpora | Algorithm | The model requires rich data and coverage of all tokens |

**Table 4. benchmark regarding MT architectures use BLEU to evaluate on 3 datasets.**

| | WMT'14(DE-EN) | Chinese-English LDC | Vietnamese-English Wikipedia |
|---|---|---|---|
| Yang et al. [31] | 0.228 | 0.466 | - |
| Wu et al. [32] | 0.347 | - | 0.093 |
| Yang et al. [33] | 0.369 | - | - |
| Zhang et al. [34] | 0.375 | 0.319 | - |
| Ahn et al. [35] | - | - | 0.341 |

**Table 5. Evaluation of the five important models in dialogue generation (DG).**

| Ref | Gen / Dis | Policy Gradient | Eval Metrics | Datasets | Innovation | Comments |
|---|---|---|---|---|---|---|
| Li et al. [2017] | LSTM/ Binary Classification | Reinforce algorithm | ERE, Perplexity | OpenSubtitles2018, NLPCC2017 | Application | there is a big discrepancy between the distributions of the generated sequences and the reference target sequences |
| Li et al. [2020] | LSTM/CNN | Reinforce algorithm | Perplexity, Accuracy | NLPCC2017 | Algorithm | This network needs to strengthen the model and evaluate more on different data |
| Olabiyi et al. [2019] | Attentional RNN/ RNN | MLE | Perplexity, BLEU, ROUGE | Movie Triples Corpus, Ubuntu Dialogue Corpus | Architecture | the large space of the model and volume of parameters is critical challenge |
| Serban et al. [2017] | Attentional RNN/ RNN | adam algorithm | BLEU | Movie Triples Corpus, Ubuntu Dialogue Corpus | Architecture | The proposed model is related to a discourse space and needs to increase the comprehensiveness of its space |
| Feng et al. [2020] | LSTM/MLP | Reinforce algorithm | BLEU, ROUGE | DailyDialog, OpenSubtitles2018 | Algorithm | This model needs improvement in the GAN network training process and can also strengthen the productive model in terms of content. |

**Table 6. Evaluation of the two important models in text summarization (TS).**

| Ref | Gen / Dis | Policy Gradient | Eval Metrics | Datasets | Innovation | Comments |
|---|---|---|---|---|---|---|
| Rekabdar et al. [2019] | LSTM / CNN | Monte Carlo Search | ROUGE | CNN/Daily Mail dataset | Application | Work on short documents and not consider context information of document |
| Vo et al. [2023] | LSTM / CNN | MLE | ROUGE | CNN/Daily Mail dataset | Architecture | Utilizing text knowledge and new word embedding models or pre-trained models can improve the output quality and cost of network training |

## 4.5. Application to Dialogue generation

Dialogue generation systems are essential components for real-world virtual assistants and chatbots, tasked with automatically generating responses to user inputs. The goal of these systems is to produce appropriate, relevant, meaningful, and human-like utterances.

One significant approach in this field involves using generative adversarial networks (GANs). For instance, in [39], an adversarial training model was created to produce unrestricted dialogue. This system, designed to pass the Turing test, trains a generative model to create sequences indistinguishable from human dialogues. The discriminator evaluates these sequences, and its output serves as a reward for the generative model. The model employs a policy gradient method and Monte Carlo search to calculate rewards, enhancing dialogue quality.

In [40], a domain-agnostic dialogue generation model was proposed to mimic human behavior. This model manages human-machine interaction through continuously trained dialogue generation policies, optimized via reinforcement learning. It uses a bidirectional gated recurrent unit (Bi-GRU) neural network and a multilayer perceptron (MLP) network to classify and calculate dialogue distributions. The generator network then creates responses based on conversation history, using an attention mechanism to highlight keywords. This approach improves response quality and dialogue coherence.

Li et al. [41] introduced a GAN-based framework for generating responses with variable emotion labels. This model includes multiple generative networks and a multi-class discriminator, allowing for emotionally diverse dialogue generation.

In [42], a methodology for training GANs on open-domain dialogue systems was presented. This model prevents dependence on specific domains and word spaces by using a weighted average model to identify the best word vectors for dialogue generation.

Serban [43] addressed challenges in dialogue generation, such as enriching the model information space and producing coherent responses, by presenting a personalized GAN. This model uses textual hierarchical modeling and speaker knowledge to improve linguistic grammar and logical coherence.

Feng et al. [44] focused on generating query-response pairs in chatbot applications. Their model considers both the context and future conversations to improve response informativeness and coherence.

Efficient neural dialogue models require extensive training data, but conventional models often add unnecessary or noisy data, which can degrade quality. Chen et al. [45] proposed a selective data augmentation (SDA) framework based on GANs. This method selects training samples based on response quality and dataset representation, resulting in targeted and more appropriate dialogues.

Overall, these advancements highlight the potential of GANs to enhance dialogue generation systems by addressing key challenges and improving the quality and coherence of generated dialogues.

### 4.6. Application to text summarization

Text summarization, a key application in natural language processing, involves automatically generating concise and meaningful summaries of text documents. Effective summarization systems must extract important information while producing coherent summaries. There are two primary approaches to text summarization: extractive and abstractive. Extractive summarization models focus on identifying and selecting important segments of the text, whereas abstractive summarization models aim to generate new, shorter content that encapsulates the main ideas of the text.

Deep neural network-based text summarization models encounter several challenges including high word repetition, long dependencies between words, and the production of unnatural or indirect summaries. To mitigate these issues, researchers have turned to generative adversarial networks (GANs).

In [46], GANs are applied to text summarization using a novel time-decay attention mechanism. Here, the generator network is trained to generate summaries that are indistinguishable from real summaries by the discriminator. This approach yields outputs that are more relevant, less repetitive, and grammatically correct compared to traditional generative models.

Yang et al. [47] introduced a GAN-based model for text summarization with multi-task constraints (PGAN-ATSMT). This model integrates additional tasks such as text categorization and syntax annotation into the GAN framework. By incorporating these auxiliary tasks, the model improves its ability to identify crucial information and generate high-quality summaries, thereby addressing issues like incomplete sentences and redundant words.

Vo [48] proposed another GAN-based method that incorporates BERT and graph convolutional networks into the generator's input. By leveraging the semantic and structural representations embedded in training documents, this model enhances the coherence and information quality of generated summaries. These advancements in GAN-based approaches signify a significant stride towards more effective and nuanced text summarization techniques.

Overall, GAN-based approaches to text summarization show promise in overcoming the limitations of traditional deep learning models, producing more accurate and coherent summaries.

## 5. Discussion

The comparative and evaluative analysis of seminal articles across various textual applications is conducted herein, delineated through distinct tables tailored to each specific application domain. Each section's initial table such as Table 1, Table 3, Table 5 and Table 6 encapsulates evaluation datasets, model innovations, and delineation of key challenges encountered within the respective models. Notably, within the realm of Generative Adversarial Networks (GANs), the pivotal constituents encompass the generator, discriminator, and policy gradient, while diverse evaluation metrics across applications are scrutinized. As elucidated in antecedent sections, the efficacy of the generator module in handling discrete data, particularly text, is impeded due to its non-differentiability, precluding direct transmission of updated gradient values via backpropagation to discrete outputs. To surmount this hurdle, the Policy Gradient [49], integrates reinforcement learning algorithms, facilitating direct backpropagation updates for discrete output segments through comprehensive network sequence rollouts. A pivotal facet within these comparative tables is the juxtaposition of principal innovations characteristic of each method. This analytical framework categorizes each model with indistinct Application/Algorithm/Architecture paradigms, thereby delineating the pioneering contributions therein. For instance, the Seqgan model stands out as the pioneer in applying GANs to text generation, marking a seminal advancement in GAN's application landscape. Moreover, it is discerned that each model has introduced novel architectural paradigms or employed diverse algorithms to enhance GAN module efficacy. Conclusively, a delineation of forthcoming research avenues is provided, underscoring the exigency to augment and consolidate existing research endeavours.

The Table 2 and Table 4 encompass a spectrum of architectural configurations assessed against the prevalent metrics across the three foremost datasets within each category. Noteworthy within this comparative analysis is the inherent challenge in adequately and accurately evaluating the presented models across each application domain. A significant impediment stems from the disparate utilization of datasets and incongruent evaluation criteria among different methodologies. For instance, within the domain of neural machine translation, a salient observation pertains to the diverse array of datasets employed, thereby engendering incongruity in evaluation. In the same translation languages, sometimes researchers have used various datasets with different volume of data. This makes it impossible to compare these methods assuming the use of the same evaluation criteria. Or in the dialogue generation section, we are faced with a variety of evaluation metrics in the methods, which makes it complicated to compare the outputs of some methods.

### 5.1. Evaluation

The standard method for evaluating the performance of Generative Adversarial Networks (GANs) remains a contentious topic. Due to the inherent structure of GANs, assessing the error rate and accuracy of the algorithm during both training and testing phases presents a formidable challenge. While some studies, such as those by [50] and [51], have proposed metrics to gauge the disparity between GAN outputs or compare distributions post-execution, these metrics still fall short of precisely capturing GAN efficiency. This challenge is particularly pronounced when GANs are employed in discrete data applications, where gauging the evolution of high scores and comparing the quality of generated data against real data prove exceedingly intricate. Nonetheless, prevailing methodologies in extant literature often rely on metrics such as Rouge, BLUE, and NLL to evaluate error rates and performance in the realm of discrete data. Despite their widespread adoption, these metrics may not fully encapsulate the nuanced intricacies of GAN performance in discrete data settings, thus highlighting the ongoing need for more comprehensive evaluation frameworks tailored to the unique challenges posed by such applications.

### 5.2. Cons

Mode collapse is perhaps the most significant issue in GAN development thus far. This means that the network generator's samples are always limited to a few specific models or structures [31]. This indicates that the output results lack the necessary range variation. In discrete data, this is manifested by repeatedly observing certain tokens of the data space in all generated samples. In recent years, some articles have attempted to address the issue by proposing solutions, such as using various types of training samples. Another set of research aimed to alter the GAN's structure, particularly the discriminator section, to improve training samples [51] through better network generator training. Another set of studies attempted to solve the problem by altering the GAN architecture and incorporating multiple generative modules. Another difficulty with GAN, which can also be seen in the application of discrete data space, is the required preparation and amount of training data set. One of the issues researchers are addressing is achieving a stable GAN [52].

### 5.3. Pros

Here is a concise summary highlighting some of the key advantages of Generative Adversarial Networks (GANs). One standout feature of GANs is their ability to operate without the need to explicitly define the shape of the probability distribution in the generative model, thus avoiding the complexity of high-dimensional models. Unlike previous generative models, GANs achieve data generation through the competitive interplay between generator and discriminator networks, rather than through explicit probability distribution calculations. In applications involving discrete data, GANs often produce superior and more precise samples compared to other statistical models like Variational Autoencoders (VAEs). Notably, the samples generated by GANs can sometimes convincingly deceive human observers, highlighting their effectiveness in generating realistic outputs.

## 6. Conclusions

This paper reviews the state-of-the-art generative adversarial networks (GANs) in the field of discrete data. The primary objective of GANs is to create new samples with high quality and variety, rather than replicating true samples. To achieve this, GANs utilize a comparison between generator and discriminator models, which are trained iteratively in an adversarial learning manner. Well-trained GANs can accurately estimate data distribution, making them widely applicable in diverse fields such as image and video generation, speech and language processing, and more.

The subsequent section focuses on the trends of GANs in discrete data, particularly in speech and language processing. This part examines different architectures and applications proposed in these fields, summarizing their evaluation metrics, advantages, and disadvantages.

This paper presents a comprehensive review of state-of-the-art Generative Adversarial Networks (GANs) in the field of discrete data. The primary goal of GANs is to generate novel samples with high quality and diversity rather than merely replicating real samples. Through an adversarial learning framework, the generator and discriminator are iteratively trained in competition, enabling well-trained GANs to accurately estimate data distributions. This capability has positioned GANs as powerful tools across various domains, including text generation, machine translation and other discrete data applications.

The paper specifically focuses on the application of GANs in discrete data generation, such as text, highlighting the unique challenges these networks face. Unlike continuous data, generating discrete values involves overcoming issues like error propagation during sequence generation. Various architectures and approaches, including reinforcement learning-based and non-RL-based methods, have been proposed to address these challenges. The review also explores the strengths and limitations of these methods, alongside the evaluation metrics used to assess their performance.

This study underscores the transformative potential of GANs in discrete data domains, while also identifying open challenges and areas for future research. By addressing these challenges, GANs can further advance the quality and applicability of generated discrete data, paving the way for innovative solutions in text generation and related fields.

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# مروری بر کاربرد شبکه مولد خصمانه در فضای داده گسسته

**علیرضا محمدی گهر[۱]، کامبیز رهبر[۱،*]، بهروز مینایی بیدگلی[۲] و ضیاالدین بهشتی فرد[۱]**

[۱] گروه مهندسی کامپیوتر، واحد تهران جنوب، دانشگاه آزاد اسلامی، تهران، ایران.

[۲] گروه مهندسی کامپیوتر، دانشگاه علم و صنعت، تهران، ایران.

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**چکیده:**

شبکه‌های مولد خصمانه (GANs) به دلیل قابلیت‌های استثنایی خود در تولید داده‌های مصنوعی، به یکی از موضوعات پژوهشی برجسته در حوزه هوش مصنوعی تبدیل شده‌اند. توانایی این شبکه‌ها در تولید داده‌های مصنوعی با کیفیت بالا باعث جلب توجه گسترده‌ای شده و به‌کارگیری آن‌ها را در حوزه‌های متنوعی نظیر تولید تصاویر و ویدئوها، طبقه‌بندی و انتقال سبک تسهیل کرده است. فراتر از این کاربردها در داده‌های پیوسته، از شبکه‌های GAN برای وظایف مرتبط با داده‌های گسسته مانند تولید متن و موسیقی نیز استفاده می‌شود. ماهیت متفاوت داده‌های پیوسته و گسسته چالش‌های خاصی را برای شبکه‌های GAN ایجاد می‌کند. به‌ویژه، تولید مقادیر گسسته نیازمند استفاده از یادگیری تقویتی در الگوریتم‌های سیاست گرادیان (Policy Gradient) تا از انتشار مستقیم خطایی که برای مقادیر پیوسته استفاده می‌شود، اجتناب شود. در این فرآیند، شبکه مولد باید متغیرهای پنهان را به حوزه‌های گسسته نگاشت کند و برخلاف تولید مقادیر پیوسته، این فرآیند شامل تنظیمات جزئی خروجی‌های شبکه مولد به‌منظور همخوانی تدریجی با داده‌های واقعی گسسته، تحت راهنمایی شبکه تمییز دهنده است. این مقاله با هدف ارائه مروری جامع بر معماری‌هایGAN ، مفاهیم بنیادی و کاربردهای آن‌ها در زمینه داده‌های گسسته نگارش شده است. همچنین به چالش‌های موجود، معیارهای ارزیابی و جهت‌گیری‌های پژوهشی آینده در این حوزه رو به رشد می‌پردازد.

**کلمات کلیدی:** شبکه مولد خصمانه، داده گسسته، تولید متن، ترجمه ماشینی، تولید دیالوگ.