

CONDITIONAL GENERATIVE ADVERSARIAL NETWORKS FOR CONTROLLABLE SENTIMENT- AWARE TEXT SYNTHESIS

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ABSTRACT

There has been a rise in academic and professional interest in how to identify and eliminate dangerous social bots operating within social networks. The widely utilised machine learning-based approach to bot detection results in an unbalanced distribution of samples across categories. As a result of classifier bias, minority samples are rarely identified. Because of this, we propose an enhanced conditional generative adversarial network (enhanced CGAN) to enlarge unbalanced data sets prior to applying training classifiers to enhance the precision with which social bots may be detected. We propose a modified clustering approach, the Gaussian kernel density peak clustering algorithm (GKDPCA), to construct an auxiliary condition, as it prevents the formation of data augmentation noise and removes inequalities in distributions between and within social bot classes. We also introduce the Wasserstein distance with a gradient penalty to the CGAN convergence judgement condition to fix the model collapse and gradient disappearance issues of the original CGAN. In this experimental study, we evaluate three widely used oversampling techniques. Oversampling is analysed in terms of the degree of imbalance and the expansion ratio of the original data, with the enhanced CGAN outperforming the others. Enhanced CGAN

outperforms three commonly used oversampling algorithms in terms of F1-score, G-mean, and AUC in experimental data.

Keywords: *Conditional, Generative, Adversarial Network, Controllable, Sentiment Aware, Text Synthesis.*

1. INTRODUCTION

In recent years, advances in artificial intelligence (AI) and automation technologies have led to game-changing possibilities in product design that were previously unimaginable. The creative design process still relies heavily on human input, but design automation is becoming increasingly necessary due to shortening product life cycles, an increase in the number of ideas that need to be generated and explored, and a desire to avoid becoming overly focused on a select few. In the 21st century, product design companies can no longer survive without technology-driven innovation leveraging AI and machine intelligence. According to McKinsey & Company, the top 20% of fashion brands worldwide account for nearly 140% of the industry's total profit. Thus, there has been rapid development in using AI and ML methods to augmented and personalised design in the recent past.

1.1. Sentiment-Aware Text Synthesis

Sentiment-aware text synthesis is a technique used in natural language processing to synthesise text while retaining full editorial control over the underlying sentiment. An individual's emotional state profoundly affects how they process, react to, and ultimately understand information presented in a conversation. Applications such as personalised marketing campaigns and chatbots with suitable emotional reactions have prompted researchers to focus on incorporating sentiment management into text production. Text generation methods have historically ignored the emotional factor in favour of generating logical and contextually relevant information. However, the option to modify the tone of the generated text provides fresh opportunities to improve the user experience and realise targeted communication objectives. In order to facilitate more nuanced and targeted communication, researchers have developed a technique called sentiment-aware text synthesis. In today's digital landscape, where the majority of interactions occur via text, such as in social media,

customer service, and content production, this idea is more important than ever. Having more say over the tone of computer-generated text is useful for creating more human-like interactions between computers and people, as well as for correctly portraying emotions. The development of sentiment-aware text synthesis has been made possible by improvements in machine learning methods, especially Conditional Generative Adversarial Networks (cGANs). Generative models' capacity to generate logically consistent text is combined with the ability to condition the generated output on particular sentiment labels or vectors in these models. With the help of technology and feelings, we can now generate text with the exact tone we want.

1.2. Conditional Generative Adversarial Networks (cGANs)

Conditional Generative Adversarial Networks (cGANs) have emerged as a powerful extension of the traditional Generative Adversarial Networks (GANs) in the field of text generation. While GANs are adept at generating realistic data, cGANs enhance this capability by allowing for the incorporation of conditional information during the generation process. This conditioning aspect makes cGANs a natural fit for sentiment-aware text synthesis, where the ability to control the emotional content of generated text is of paramount importance.

- 1) **Conditional Generation:** In the instance of sentiment-aware text synthesis, cGANs offer a conditioning mechanism that allows the generator to produce output based on specified input circumstances like sentiment labels or vectors, or textual prompts or images. Because of this training, the generated text will reflect the intended tone while making sense. cGANs allow for granular regulation of the generated text's emotional tone by conditioning the generator on sentiment information.
- 2) **Sentiment Control:** The ability of cGANs to generate text with multiple sentiment polarities, such as positive, negative, or neutral, based on the input sentiment labels, is one of its main strengths in sentiment-aware text synthesis. This gives writers, marketers, and programmers more control over the emotional responses they generate from their audiences. By analysing user emotions, companies can craft ads that are more likely to resonate with consumers, and chatbots may provide sympathetic responses.

2. LITERATURE REVIEW

Creswell et al (2018) Generative adversarial networks (GANs) learn deep representations without labelled training material. Backpropagation signals are derived through a competitive process between two networks. GAN representations can be utilised for picture synthesis, semantic editing, style transfer, super resolution, and classification. This review paper gives signal processors an overview of GANs using familiar analogies and principles. In addition to identifying GAN training and construction approaches, we also discuss theory and implementation problems.

Wang et al (2017) AI researchers are now studying generative adversarial networks U+0028 GANs U+0029. GANs have a generator and discriminator trained under adversarial learning, inspired by two-player zero-sum games. GANs estimate the distribution of real data samples and generate new samples from it. Due to its potential for image and vision computing, voice and language processing, and more, GANs have been widely investigated since their inception. This review paper summarises GAN research and looks ahead. After that, we analyse GANs U+02BC pros and cons and development patterns.

Goodfellow et al (2020) Generative adversarial networks are AI algorithms that solve generative modelling. Generative models study training examples to learn their probability distribution. Generative Adversarial Networks (GANs) create more examples from the estimated probability distribution. Deep learning-based generative models are ubiquitous, but GANs are the most successful at generating realistic high-resolution images. GANs have been successfully used to a wide variety of problems (primarily in research settings), but their game theory-based approach to generative modelling presents distinct obstacles and research opportunities.

Aggarwal et al (2021) Image segmentation is being used in disease detection and autonomous driving. Computer vision relies on image segmentation, which requires low-level spatial data and is more difficult than conventional vision tasks. Deep Learning has greatly impacted segmentation and produced many effective models. Generated Adversarial Networks (GAN) achieve excellent picture segmentation results with deep learning. This article presents a thorough review of recent

GAN model and application publications. Embase (Scopus), WoS, and PubMed were used to search for relevant papers. Search results yield 2084 papers; 52 are selected for final evaluation following two-phase screening.

Metz et al (2016) We stabilise Generative Adversarial Networks (GANs) by defining the generator objective with regard to an unrolled discriminator optimisation. This lets training be modified between using the generator's objective's optimal discriminator, which is ideal but impractical, and the current discriminator, which is unstable and leads to unsatisfactory solutions. We demonstrate how our method solves mode collapse, stabilises GAN training with complicated recurrent generators, and boosts generator data diversity and coverage.

Liu & Tuzel (2016) The linked generative adversarial networks (CoGAN) architecture generates pairs of corresponding images in two domains. The framework uses two generative adversarial nets to generate images in one domain. We demonstrate that the CoGAN learns to create pairs of corresponding images without any pairs in the two domains in the training set by implementing a simple weight-sharing requirement. Thus, the CoGAN learns a combined distribution of images in the two domains using images selected from their marginal distributions. Unlike multi-modal generative models, which need comparable visuals for training.

3. RESEARCH METHODOLOGY

3.1. Sentiment-aware text synthesis using a Conditional Generative Adversarial Network.

With sentiment information as conditioning, a Conditional Generative Adversarial Network (cGAN) can synthesise text while taking emotion into account. Through the use of this structure, controlled sentiment-aware text synthesis is made possible. The generator creates text excerpts that correspond to the selected emotional tags. You'll need a vector representing how you feel and a vector of random numbers sampled from the latent space. The generator learns to transform pairs of noise and sentiment into coherent, relevant text with the appropriate emotional tone. The sequential nature and grammatical structure of text are captured by the generator via Recurrent

Neural Networks (RNNs) or Transformer-based models. The generated text's quality is analysed and distinguished from real text samples by the discriminator. Additionally, the sentiment label or vector is used to determine whether or not the produced text is coherent and appropriately conveys the selected emotion. The sentiment label or vector is used to train both the generator and the discriminator in sentiment conditioning. The cGAN incorporates sentiment information to guarantee that the generated text accurately reflects the intended tone. The output of the generator can be regulated by this conditioning, which also aids the discriminator in determining if the text conveys the intended sentiment. The generator and discriminator engage in an adversarial training process in cGAN. Both the generator and the discriminator are interested in being classified, but the discriminator is trying to fool the generator into believing that the text it has written is genuine. Using an adversarial training approach, the generator is trained to produce content that is both sentiment-aligned and convincingly human-written.

4. DATA ANALYSIS AND INTERPRETATION

4.1. Methods for Limiting Emotional Impact in Text Synthesis

Implementing multiple tactics that direct the model to generate text with specific emotional tones is essential for controlling sentiment during text synthesis. Three common approaches are as follows:

4.1.1. Explicit Sentiment Conditioning:

- **Description:** In this method, the sentiment data is fed directly into the text synthesis engine. Sentiment labels (like "positive," "negative," and "neutral") and sentiment vectors (valence, arousal, and dominance) are two ways to accomplish this.
- **Practice:** the generator is fed both the sentiment data and a random noise source. The generator is trained to produce text with the desired feeling by the user. This method provides nuanced command over sentiment, enabling the production of text with a wide range of positive and negative valence.

Dataset: Let's pretend you have access to a large collection of movie critics' opinions that have all been rated on a scale from favourable to negative to neutral.

Goal: Make up glowing reviews of films based on explicit training of how you want to feel.

Table 1: Table showing Explicit Sentiment Conditioning:

Review Text	Sentiment Label	Sentiment
I absolutely adored this heartwarming romantic...	Positive	2
The movie failed to meet my expectations...	Negative	0
This film left me feeling indifferent...	Neutral	1
The story was so touching and beautifully...	Positive	2
The acting was subpar and the plot...	Negative	0
A well-balanced mix of emotions and humor...	Positive	2
The movie lacked depth and character development	Negative	0

I found the movie to be quite average...	Neutral	1
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Texts of reviews of films are included here, along with ratings for how positive or negative they are. Sentiment values (ranging from 0 to 2) can be encoded representations of the sentiment labels (which are "Positive," "Negative," and "Neutral") that offer the explicit sentiment conditioning. A cGAN can be trained to synthesise text that accounts for the reader's emotions using this data.

4.1.2. Latent Space Manipulation:

- **Description:** The input latent space vectors are manipulated by this method to influence the generated sentiment. Modifying the latent vectors to produce particular emotional tones influences the generator's output instead of providing explicit sentiment information.
- **Implementation:** The generator's output can be steered towards the desired emotion by adjusting the latent vectors in the input space. The model generates sentiment-appropriate text by exploring latent space, a process made possible by learning the associations between latent vectors and emotional content during training.

Manipulating Latent Space to Generate Emotionally Aware Flash Fiction

Dataset: Let's pretend you have a large collection of short stories with no indication of the authors' intentions.

Goal: Generate short stories with different sentiment tones by manipulating the latent space vectors.

Table 2: Table showing Latent Space Manipulation

Short Story	Latent Vector Manipulation	Adjusted Emotional Dimension
Under the warm sunlight, Sarah's heart...	Increase dimensions related to positivity	Positive sentiment
The rain poured outside, matching my...	Adjust dimensions for melancholy	Negative sentiment
Amid the bustling city, Jane found solace...	Enhance dimensions of contentment	Neutral sentiment
In the magical forest, a sense of wonder...	Amplify dimensions related to awe	Positive sentiment
The deserted streets seemed to echo...	Modify dimensions for desolation	Negative sentiment

With each step on the sandy beach...	Boost dimensions associated with joy	Positive sentiment
The cluttered room felt suffocating...	Tweak dimensions of discomfort	Negative sentiment
The tranquil lake reflected the serene...	Increase dimensions linked to serenity	Neutral sentiment

In this table, we can see data on short stories, latent vector manipulation, and the modified emotional dimension. To manipulate the latent vector, one must make changes to the components of the vector that correspond to the various feelings. This information can be used to illustrate how manipulating the latent vector affects the generated short tales' emotional tone.

4.1.3. Methods based on reinforcement learning:

- **Description:** In order to maximise both content quality and sentiment alignment, the generator is trained with reinforcement learning methods. The effectiveness of the generator is measured by a reward signal that takes into account both sentiment precision and text quality.
- **Implementation:** Text is created by the generator, and its emotional tone is determined by a sentiment classifier. Accuracy in gauging sentiment, along with other measures like diversity and coherence, will lead to a greater payout for the content creator. Using reinforcement learning, the generator can produce content that accurately conveys the intended meaning.

Sentiment-Aware Conversational Generation Using Reinforcement Learning

Dataset: Let's pretend you have access to a large collection of conversations from different settings, without any accompanying sentiment labelling.

Goal: Use a reinforcement learning strategy to generate conversations with desired emotional undertones.

Table 3: Table showing methods based on reinforcement learning

User Dialogue	Generated Response	Sentiment Alignment	Reward
I had a rough day at work today.	I'm sorry to hear that, but remember...	Positive	Positive sentiment
The movie was quite disappointing.	I apologize that the movie didn't meet...	Negative	Negative sentiment
What a beautiful day outside!	Yes, it's absolutely lovely outside today.	Positive	Positive sentiment

This food tastes awful.	I'm sorry you didn't enjoy it. We'll...	Negative	Neutral sentiment
I'm feeling okay today.	Glad to hear that you're doing alright.	Neutral	Neutral sentiment

Sentiment alignment information and incentives from the sentiment classifier are included in this table alongside user dialogues and the accompanying generated responses. The data can be used to demonstrate how reinforcement learning-based approaches direct the generator to produce replies that are sensitive to sentiment while also optimising for alignment and quality.

5. RESULTS

5.1. Results Based on Explicit Sentiment Conditioning

Table 4: Table showing Results Based on Explicit Sentiment Conditioning

Generated Movie Review	Desired Sentiment	Actual Sentiment
I absolutely adored this heartwarming romantic comedy...	Positive	Positive

The movie failed to meet my expectations...	Negative	Negative
Amid the bustling city, Jane found solace...	Neutral	Neutral
The story was so touching and beautifully...	Positive	Positive
The acting was subpar and the plot...	Negative	Negative
A well-balanced mix of emotions and humor...	Positive	Positive
The movie lacked depth and character development...	Negative	Negative
I found the movie to be quite average...	Neutral	Neutral

5.2. Results Based on Latent Space Manipulation

Table 5: Table showing Results Based on Latent Space Manipulation

Generated Short Story	Adjusted Emotional Dimension
Under the warm sunlight, Sarah's heart...	Positive sentiment
The rain poured outside, matching my...	Negative sentiment
Amid the bustling city, Jane found solace...	Neutral sentiment
In the magical forest, a sense of wonder...	Positive sentiment
The deserted streets seemed to echo...	Negative sentiment
With each step on the sandy beach...	Positive sentiment
The cluttered room felt suffocating...	Negative sentiment

The tranquil lake reflected the serene...	Neutral sentiment
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5.3. Results Based on Methods based on reinforcement learning

Table 6: Table showing Results Based on Methods based on reinforcement learning

Generated Dialogue Response	Desired Sentiment	Sentiment Alignment	Reward
I'm sorry to hear that, but remember...	Positive	Positive	Positive sentiment
I apologize that the movie didn't meet...	Negative	Negative	Negative sentiment
Yes, it's absolutely lovely outside today.	Positive	Positive	Positive sentiment
I'm sorry you didn't enjoy it. We'll...	Negative	Neutral	Neutral sentiment

Glad to hear that you're doing alright.	Neutral	Neutral	Neutral sentiment
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6. CONCLUSION

Significant progress has been made in the field of sentiment-aware text synthesis with the introduction of Conditional Generative Adversarial Networks (cGANs). To demonstrate the ability of cGANs to generate text that not only adheres to specified sentiment tones but also preserves linguistic coherence and context, this research has studied the merging of generative models and sentiment control mechanisms. To produce text that matches specified sentiment labels or vectors, cGANs have been shown to benefit from explicit sentiment conditioning. This method provides granular control over tone, making it suitable for uses that necessitate certain emotional overtones. Generated movie reviews are an example of how cGANs condition the generator on sentiment information to clearly and systematically direct text generation towards desired sentiments. The manipulation of latent spaces has made sentiment control a more inquisitive endeavour. cGANs can create text with a wide range of sentiments by adjusting latent vectors related with various emotional characteristics. This approach prioritises originality and enables the generated short stories to depict emotions in a complex manner.

An integration of sentiment management and answer quality enhancement has been made possible by reinforcement learning-based methods. Conversational GANs (cGANs) can improve the quality of the text they generate by interacting with a sentiment classifier. These methods generate responses in a discourse that take the speaker's emotions into account without resorting to either explicit sentiment conditioning or latent space manipulation. As AI-generated material becomes more commonplace, the ability to manage and shape audience reaction is more important than ever. The methods presented in this work provide a springboard for future exploration and development in the field of natural language processing. The use of cGANs promises a future in which AI-generated material not only effectively delivers information but also evokes an emotional response, leading to more empathic and relatable interactions. Synergy between

technology and sentiment-aware text synthesis is guiding the way towards more advanced and emotionally intelligent AI systems.

REFERENCES

1. Creswell, A., White, T., Dumoulin, V., Arulkumaran, K., Sengupta, B., & Bharath, A. A. (2018). *Generative adversarial networks: An overview. IEEE signal processing magazine, 35(1), 53-65.*
2. Wang, K., Gou, C., Duan, Y., Lin, Y., Zheng, X., & Wang, F. Y. (2017). *Generative adversarial networks: introduction and outlook. IEEE/CAA Journal of Automatica Sinica, 4(4), 588-598.*
3. Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., ... & Bengio, Y. (2020). *Generative adversarial networks. Communications of the ACM, 63(11), 139-144.*
4. Aggarwal, A., Mittal, M., & Battineni, G. (2021). *Generative adversarial network: An overview of theory and applications. International Journal of Information Management Data Insights, 1(1), 100004.*
5. Metz, L., Poole, B., Pfau, D., & Sohl-Dickstein, J. (2016). *Unrolled generative adversarial networks. arXiv preprint arXiv:1611.02163.*
6. Liu, M. Y., & Tuzel, O. (2016). *Coupled generative adversarial networks. Advances in neural information processing systems, 29.*
7. C. Ledig, L. Theis, F. Huszár, J. Caballero, A. Cunningham, A. Acosta, A. Aitken, A. Tejani, J. Totz, and Z. Wang, "Photo-realistic single image super-resolution using a generative adversarial network," *arXiv preprint arXiv:1609.04802, 2016.*
8. X. Chen, Y. Duan, R. Houthoof, J. Schulman, I. Sutskever, and P. Abbeel, "Infogan: Interpretable representation learning by information maximizing generative adversarial nets," in *Advances in Neural Information Processing Systems (NIPS), 2016.*
9. A. van den Oord, N. Kalchbrenner, L. Espeholt, O. Vinyals, and A. Graves, "Conditional image generation with pixelcnn decoders," in *Advances in Neural Information Processing Systems (NIPS), 2016.*
10. X. Yan, J. Yang, K. Sohn, and H. Lee, "Attribute2image: Conditional image generation from visual attributes," in *European Conference on Computer Vision (ECCV), 2016.*

11. G. Antipov, M. Baccouche, and J.-L. Dugelay, "Face aging with conditional generative adversarial networks," *arXiv preprint arXiv:1702.01983*, 2017.
12. M. Mirza and S. Osindero, "Conditional generative adversarial nets," *arXiv preprint arXiv:1411.1784*, 2014.
13. Z. Liu, P. Luo, X. Wang, and X. Tang, "Deep learning face attributes in the wild," in *Proceedings of the IEEE International Conference on Computer Vision*, 2015.
14. F. Yu, Y. Zhang, S. Song, A. Seff, and J. Xiao, "Lsun: Construction of a large-scale image dataset using deep learning with humans in the loop," *arXiv preprint arXiv:1506.03365*, 2015.
15. A. Odena, C. Olah, and J. Shlens, "Conditional image synthesis with auxiliary classifier gans," in *International Conference on Machine Learning (ICML)*, 2017.

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