Controlled Text Generation with Large Language Models in Natural Language Processing: A Survey

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Abstract

Controlled text generation (CTG) represents a pivotal advancement in natural language processing (NLP), leveraging large language models (LLMs) to produce text that adheres to specific constraints or user-defined attributes. This survey explores the role of LLMs in CTG, highlighting their transformative impact on text generation tasks through architectures like GPT-3 and BERT. These models facilitate the production of coherent and contextually relevant narratives, yet face challenges such as unpredictability and resource-intensive fine-tuning. The survey outlines various CTG techniques, including prompt engineering, language model fine-tuning, reinforcement learning, and constraint-based methods, emphasizing their role in enhancing the precision and adaptability of LLMs. Practical applications span education, healthcare, content creation, and more, showcasing CTG's versatility across diverse domains. However, ethical concerns, computational constraints, and limitations in maintaining long-term coherence present significant challenges. Future directions focus on enhancing model architecture, advanced control mechanisms, and ethical considerations to mitigate biases and misuse potential. The survey concludes that ongoing research is essential for advancing CTG, ensuring it meets the growing demand for high-quality, user-aligned text generation in NLP.

1 Introduction

1.1 Concept and Significance of Controlled Text Generation

Controlled text generation marks a pivotal advancement in natural language processing (NLP), enabling the production of text that conforms to specific constraints or user-defined attributes. This capability is essential for applications necessitating tailored communication, significantly enhancing user experience and satisfaction. The growing demand for accurate control mechanisms in text generation underscores its critical role in NLP [1]. By guiding large language models (LLMs), controlled text generation addresses inefficiencies in existing autoregressive models, which often yield suboptimal syntactic structures and diminished diversity [2].

The importance of controlled text generation lies in its ability to maintain fluency and coherence while adhering to specified constraints. This ensures that the generated text is not only relevant and fluent but also aligns with user intentions, particularly in scenarios requiring customization of attributes such as sentiment and readability [3]. Furthermore, it plays a vital role in producing emotionally nuanced text while preserving grammatical integrity, thereby enhancing the quality and impact of the generated content.

Controlled text generation is also crucial in mitigating the misuse of NLP systems, such as the creation of deceptive content like fake news and misinformation. By enforcing adherence to specific rules and constraints, it improves the reliability and relevance of outputs. The text generation landscape is evolving to address significant challenges in enhancing creativity and fairness, especially in open-domain contexts. This includes maintaining long-term coherence in generated content and mitigating social biases arising from training data. Traditional models often rely on surface

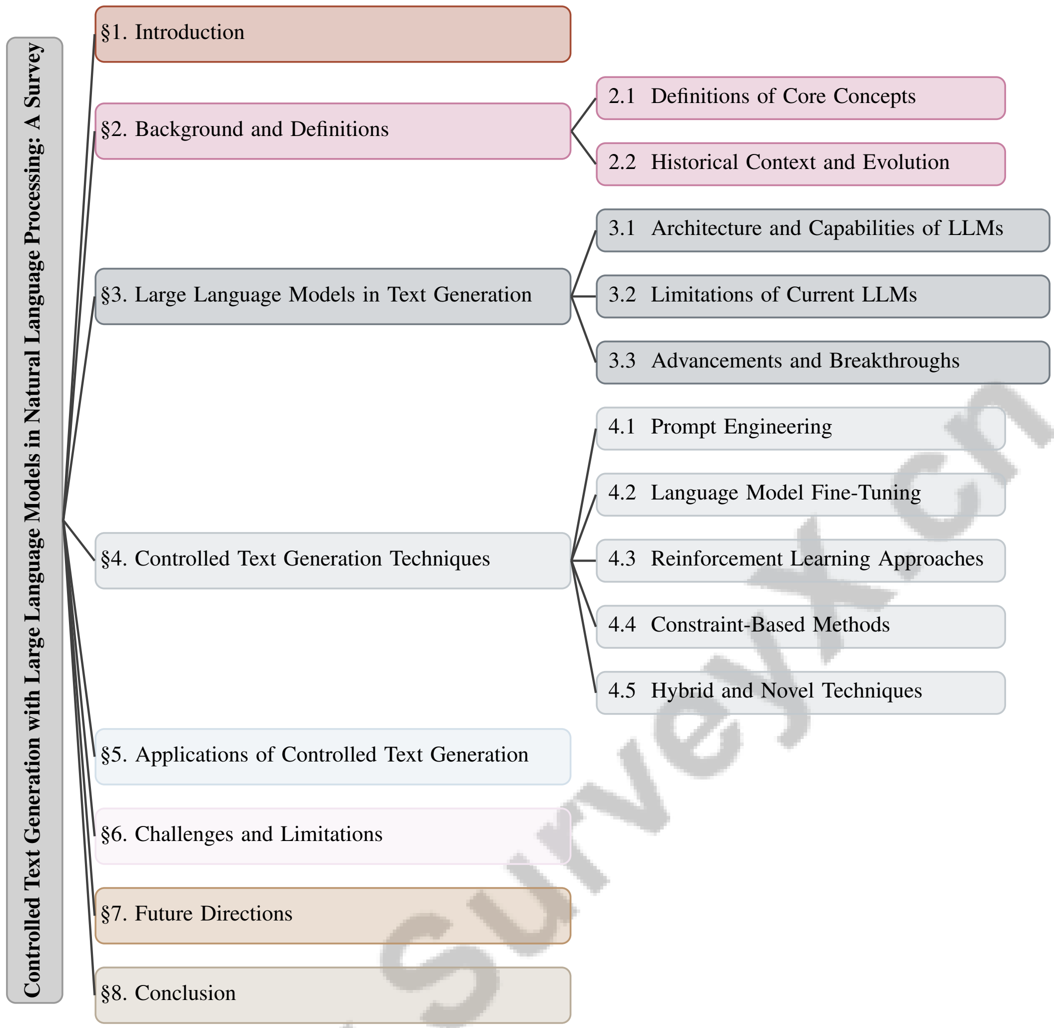

Figure 1: chapter structure

patterns rather than deeper semantic understanding, limiting their effectiveness in open-ended tasks. Recent advancements in controllable text generation techniques, such as hierarchical generation and constrained decoding, aim to improve creative outputs—like stories and poetry—while addressing bias mitigation. Ongoing research emphasizes the integration of diverse knowledge forms into text generation models to enhance performance and relevance in real-world applications [4, 5, 6, 7, 8].

As the demand for personalized and context-aware communication grows across various domains, controlled text generation remains a pivotal area of research and development. The incorporation of structured frameworks, such as the Writing Path, into NLP systems significantly enhances their capacity to generate high-quality, goal-oriented text that aligns with user specifications. This advancement not only improves coherence, contextual accuracy, and grammatical correctness but also addresses critical challenges in text generation, such as bias and reasoning difficulties. Consequently, these innovations reinforce the role of NLP technologies in meeting the diverse and evolving needs of users across applications, from automated content creation to customer service and educational tools [9, 5, 10, 8, 11].

1.2 Role of Large Language Models (LLMs) in Controlled Text Generation

Large Language Models (LLMs) are integral to the advancement of controlled text generation, primarily due to their ability to transform structured inputs into coherent, contextually relevant narratives. Models based on transformer architectures, such as GPT-2 and GPT-3, exemplify the potential of LLMs in generating fluent and contextually accurate text [11]. The hierarchical generation framework proposed by [7] illustrates how separating content planning from surface realization can enhance creativity and coherence, showcasing LLMs' capabilities in structured text generation.

The adaptability of LLMs is further evidenced by the Neural Rule-Execution Tracking Machine (NRETM), which enhances the controllability of transformer-based neural text generation models [12]. This approach underscores the significance of LLMs in providing users with greater control over generated content, a critical aspect of controlled text generation. Similarly, the GENPET method leverages pretrained language models to improve text generation efficiency, further emphasizing the crucial role of LLMs in this domain [13].

In terms of emotional and semantic control, the Affective Text Generation Model (ATGM) adapts the GPT-2 architecture, allowing users to control both the category and intensity of emotion in the generated text [3]. This flexibility is vital for producing emotionally nuanced content. Additionally, Tailor, a semantically-controlled text generation system, employs control codes derived from semantic representations to guide output generation, further illustrating the role of LLMs in controlled text generation [2].

Despite their robust capabilities, LLMs face challenges related to unpredictability and resource-intensive fine-tuning [11]. To address these challenges, lightweight frameworks like LiFi, which utilize fine-grained control codes, have been proposed to enhance LLM controllability without extensive computational resources [1]. These advancements highlight the ongoing evolution of LLMs in controlled text generation, emphasizing their significance in producing high-quality, user-aligned text with specified attributes.

1.3 Objectives of the Survey

This survey aims to provide a comprehensive overview of controlled text generation (CTG) and its applications, particularly focusing on the role of large language models (LLMs). By systematically reviewing the current state of CTG, the survey addresses existing knowledge gaps and offers insights into various text generation tasks and their associated challenges [5]. Additionally, it highlights the implications of AI-generated text on human rights and political stability, emphasizing the need for heightened awareness of potential risks [14].

Another key goal is to explore the scenarios and methods through which tools enhance the capabilities of language models in performing complex tasks, thereby expanding the practical applications of CTG [15]. The survey also introduces innovative methods, such as BOLT, which improve the efficiency of controlled text generation by utilizing tunable biases in pretrained language models (PLMs) [16]. Through a systematic critical review, this survey intends to deepen understanding of current approaches, tasks, and evaluation methods in CTG, ultimately contributing to the advancement of this field [17].

1.4 Structure of the Survey

This survey is structured to systematically explore the multifaceted domain of controlled text generation (CTG), with an emphasis on the role of large language models (LLMs). It begins with an introduction that establishes the significance and objectives of CTG, followed by a detailed background section defining core concepts and tracing their historical evolution. The subsequent section examines the architecture, capabilities, and limitations of LLMs, highlighting significant advancements that have influenced text generation.

Following this foundational overview, the survey investigates various techniques employed in controlled text generation, including prompt engineering, language model fine-tuning, reinforcement learning approaches, and constraint-based methods. This section also explores hybrid and novel techniques, providing a comprehensive understanding of the methodologies used to guide LLMs in producing text with specific attributes or constraints.

The practical applications of CTG are explored across sectors such as education—where it alleviates teachers' workloads by generating high-quality, tailored questions; healthcare—where it aids in creating personalized patient communication; content creation—enabling efficient production of engaging material; business process management—streamlining documentation and reporting; and media and entertainment—enhancing scriptwriting and interactive narratives. This exploration underscores the versatility and transformative potential of CTG across various fields [4, 5, 18, 19, 20].

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The survey also addresses challenges and limitations associated with CTG, including ethical concerns, computational constraints, and difficulties in maintaining text quality while enforcing constraints. Engaging in these discussions is essential for identifying and addressing current barriers to effective implementation of CTG, particularly in light of challenges highlighted in recent literature, such as bias, reasoning, and dataset availability that hinder progress in the field [5, 21, 18].

Finally, the survey concludes with a section on future directions, exploring potential research advancements, emerging trends, and the ethical and societal implications of CTG. By providing a comprehensive overview of the current state and future prospects of controlled text generation, this survey aims to contribute to the ongoing discourse in the field and guide future research efforts.The following sections are organized as shown in Figure 1.

2 Background and Definitions

2.1 Definitions of Core Concepts

Controlled text generation (CTG) is an essential facet of natural language processing (NLP) that focuses on generating text under specific constraints like sentiment, style, or factual accuracy [1]. Unlike traditional text generation, CTG ensures adherence to semantic, syntactic, or stylistic guidelines, crucial for maintaining narrative coherence and catering to diverse readability levels based on users' educational backgrounds [22, 3]. Large language models (LLMs) such as GPT-3 and BERT are pivotal in CTG, facilitating coherent and contextually relevant text generation across tasks like summarization, translation, and question answering [12]. However, challenges occur when generated text diverges from training data distribution, necessitating the integration of structured and unstructured knowledge bases to enhance adaptability [2]. Long-term content planning also presents a challenge in multi-sentence text generation [23].

Key CTG concepts include faithfulness, factual consistency, and Natural Language Generation (NLG), which ensure the accuracy and reliability of generated content [13]. Emotion-conditioned text generation utilizes extensive datasets and computational power for nuanced emotional control [3]. CTG also guides outputs to avoid undesirable content while maintaining quality [11]. Prompt engineering is fundamental, employing techniques like prompt template engineering and multi-turn prompting to refine generation, especially in low-resource settings [24]. CTG tackles generating text adhering to specific constraints, such as numerical planning, evaluated by relevant benchmarks [22].

Controlled table-to-text generation transforms tabular data into textual narratives based on user input, with definitions extending to automated speech generation and disinformation, highlighting CTG's role in political contexts [2]. CTG's capacity to produce controlled, high-quality text across domains underscores its importance in advancing NLP technologies, ensuring alignment with user-defined constraints and attributes [1]. Definitions also cover internal and external knowledge enhancements, including topics, keywords, knowledge bases, and knowledge graphs, addressing challenges in generating concise text from multiple similar messages without sacrificing clarity [22].

CTG is further defined as generating coherent and diverse long texts from structured data, particularly in applications like product descriptions and recipe generation [25]. This involves crafting narratives from key facts while adhering to them throughout [24]. CTG also involves generative models producing text in multiple styles, overcoming limitations of models that generate text in a fixed style [25]. The inefficiencies and inflexibility of current NLG methods, often relying on complex linguistic components or rigid templates, highlight the need for more adaptable CTG approaches [22].

2.2 Historical Context and Evolution

The evolution of controlled text generation (CTG) and large language models (LLMs) is intertwined with the broader development of natural language processing (NLP) and deep learning, particularly transformer-based models [17]. Early CTG methods, characterized by rule-based and template-based approaches, were limited in flexibility and adaptability to complex tasks [22]. These methods often depended on manually crafted logical forms and templates, which were costly and impractical for dynamic applications [26].

The advent of Long Short-Term Memory (LSTM) networks marked a significant step forward, enhancing context retention over longer sequences. However, the development of the Transformer architecture revolutionized the field, enabling the modeling of dependencies between words regardless of their positions, thus forming the foundation for modern NLP and leading to powerful LLMs like BERT and GPT [17]. The shift to pretrained language models (PLMs) was pivotal, improving contextually relevant and coherent text generation across applications. Despite advancements, the probabilistic nature of these models posed challenges in controlling generated text to include specific words or attributes, highlighting the need for innovative control mechanisms [27]. The emergence of LLMs has raised concerns about factual inaccuracies and hallucinations, necessitating methods to quantify uncertainty in outputs [28].

CTG methods have evolved to include both training-stage approaches, such as retraining and fine-tuning, and inference-stage techniques, including prompt engineering and latent space manipulation [25]. Traditional NLP approaches often struggled with expressiveness and constraint satisfaction, leading to a recognition of the need for more comprehensive methods integrating multiple controllability aspects [4]. The historical context of CTG also encompasses the evolution of evaluation methods for NLG systems, which faced significant challenges due to differences between domain-oriented and linguistically motivated ontologies [29]. Traditional methods often lacked the ability to modulate specific attribute intensity, resulting in ineffective responses [30]. Furthermore, traditional algorithms faced scaling challenges with data size, leading to bottlenecks in data retrieval and processing [31].

Recently, the focus has shifted towards more efficient and adaptable approaches to overcome early methods' limitations while addressing new challenges. The historical context of NLG has also evolved concerning digital deception and challenges in detecting deceptive practices [32]. Existing benchmarks for constrained text generation often emphasize fixed constraint types, which state-of-the-art models like GPT-4 can handle with relative ease [33].

The evolution of CTG and LLMs remains driven by the need to enhance model architectures, control mechanisms, and evaluation strategies, aiming to develop robust and adaptable systems capable of meeting diverse user demands across domains [34].

3 Large Language Models in Text Generation

3.1 Architecture and Capabilities of LLMs

Large Language Models (LLMs) have revolutionized text generation through their advanced architectures, particularly the Transformer model, which excels at capturing complex text dependencies via its self-attention mechanism. This architecture supports models like GPT-2, GPT-3, and BERT, facilitating the generation of coherent narratives through autoregressive and bidirectional context representations [35]. Dynamic prompts, such as CONTROL PREFIXES, further enhance model outputs by incorporating minimal additional parameters tailored to specific input attributes [1].

LLMs integrate diverse methodologies, including the Neural Rule-Execution Tracking Machine (NRETM), which combines predicate logic with transformer-based generators to guide the generation process [12]. The Affective Text Generation Model (ATGM) optimizes emotional intensity and grammaticality through a perturbation mechanism, showcasing fine-grained control over outputs [3]. Similarly, Tailor employs a pretrained seq2seq model to manage various perturbations via structured control codes, demonstrating LLMs' flexibility in adapting to user-defined attributes [2].

Innovative frameworks like Writing Path enhance content generation control by utilizing explicit outlines, guiding LLMs to produce high-quality text [7]. The RSA-Control method leverages mutual reasoning between a speaker and listener to improve attribute control in text generation, emphasizing pragmatic aspects of language [34]. Furthermore, LLMs benefit from external information sources, such as structured knowledge graphs (KGs) and unstructured knowledge bases (KBs), which provide additional context and factual accuracy, enhancing generation capabilities [32].

Advanced methodologies like the Plan-to-Text Generation (P2T) method separate text planning from realization, leading to more coherent outputs through a higher-level understanding of narrative structure [7]. The Conditional Variational Auto-Encoder (CVAE) exemplifies the architecture's ability to balance accuracy, diversity, and novelty in phrase generation, adapting to various stylistic and semantic constraints [3].

As illustrated in Figure 2, this figure illustrates the architecture and capabilities of Large Language Models (LLMs), featuring advanced architectures, control techniques, and innovative methodologies that enhance text generation quality and relevance. The visual examples highlight the multifaceted nature of these models and their applications. The first example, "Math Problem Solving with a Brain and Calculator," metaphorically depicts the interactions between human cognition and computational tools in solving complex mathematical equations, emphasizing the supportive role of text generation modules. The second example, "Vector Representation in a 3D Space," visually conveys the concept of vector scaling, showcasing how central vectors can be transformed at various magnitudes, essential for understanding LLMs' spatial capabilities. The third example shifts focus to text summarization, depicting a flowchart from initial instruction to final prompt processing by advanced models like Llama 2, emphasizing the evolution of text generation from traditional summarization techniques to innovative approaches. Collectively, these examples underscore the diverse architectural elements and capabilities of LLMs, as well as their potential in addressing complex tasks across various domains [15, 36, 37].

LLMs are characterized by their sophisticated architecture and capabilities, enabling the integration of methodologies such as knowledge access, dynamic prompt adaptation, and structured writing techniques. These features significantly enhance the quality and relevance of text generation by allowing systematic input manipulation, explicit outlines for goal-oriented writing, and control over attribute intensity across diverse contexts, thereby improving the overall effectiveness of natural language generation tasks [30, 38, 10, 37]. As these models evolve, their architecture will likely expand, offering more sophisticated solutions for controlled text generation across various applications.

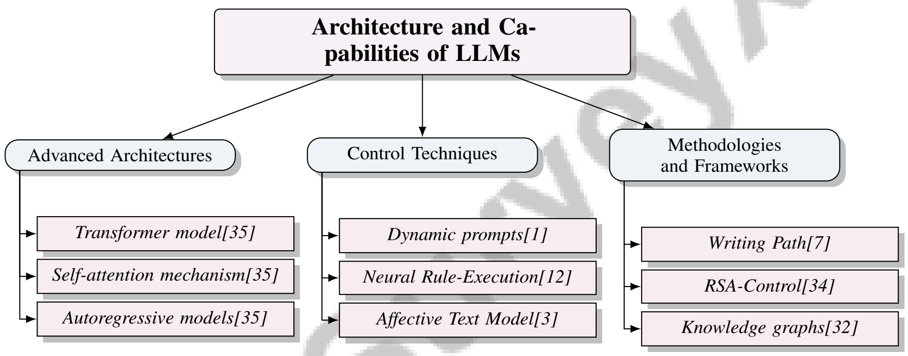

Figure 2: This figure illustrates the architecture and capabilities of Large Language Models (LLMs), featuring advanced architectures, control techniques, and innovative methodologies that enhance text generation quality and relevance.

3.2 Limitations of Current LLMs

LLMs encounter several limitations that affect their effectiveness in controlled text generation, primarily due to their reliance on extensive training data, which is often scarce for less-resourced languages, thus limiting multilingual capabilities [34]. This reliance can lead to overfitting, particularly when fine-tuning on limited datasets, resulting in hallucinated outputs that lack factual accuracy [28]. Moreover, existing benchmarks inadequately address uncertainty across diverse prompts, potentially causing output miscalibration [39].

The black-box nature of LLMs poses significant challenges in ensuring that generated texts adhere to specific control attributes, often necessitating extensive computational resources for fine-tuning, which can yield unexpected outputs [34]. Current controlled text generation methods also struggle to preserve original content, particularly with black-box models, leading to a trade-off between emotional expressiveness and grammatical correctness.

In terms of computational efficiency, LLMs suffer from low inference efficiency and noise due to heuristic scoring functions prevalent in search-based techniques [22]. The preprocessing step that binarizes dependency trees can hinder parallelism, negatively affecting performance on complex constructions [40]. Additionally, the trade-off between emotional expressiveness and grammatical correctness remains a significant limitation, as models often compromise one for the other [3].

Architectural constraints, particularly in maintaining coherence over long dependencies, exacerbate these issues, resulting in incoherent sentence generation [23]. The lack of explicit content order

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modeling in neural network-based approaches further limits fluency and coherence compared to human writing [17]. These challenges highlight the necessity for advancements in model architecture, data efficiency, and semantic understanding to enhance LLMs' capabilities in generating reliable, coherent, and contextually relevant text across diverse applications.

3.3 Advancements and Breakthroughs

Recent advancements in LLMs have significantly impacted text generation, leading to more sophisticated control over generated content. A notable development is TextBox 2.0, which has demonstrated competitive performance by surpassing original implementations across various metrics [41], underscoring ongoing improvements in model architectures and capabilities.

The introduction of model arithmetic marks a pivotal advancement in controlled text generation, enabling precise control over outputs by blending multiple models and attributes, thereby aligning generated text closely with user-defined specifications [42]. Such innovations highlight the potential of arithmetic operations to enhance LLM adaptability and precision, facilitating the generation of content that meets specific constraints or stylistic requirements.

Transformers, the foundational architecture behind many LLMs, have reshaped natural language generation (NLG) standards, enabling sophisticated applications across various domains [43]. Their ability to capture complex dependencies within text has been instrumental in advancing the fluency and coherence of generated narratives, thus broadening LLM applicability.

Recent advancements in LLMs illustrate the rapidly evolving landscape of NLG, showcasing unprecedented flexibility in executing complex tasks and enhancing user-driven content creation. These innovations address challenges in defining and evaluating diverse NLG tasks—such as citation text generation and structured writing—while introducing new frameworks and methodologies that improve the quality and alignment of generated text with user intentions. Systematic literature reviews reveal ongoing challenges, including issues related to bias, reasoning, and evaluation metrics, emphasizing the need for continued exploration and refinement in LLM capabilities to push the boundaries of text generation [5, 10, 37, 4]. As models become more adept at managing control attributes and generating contextually relevant text, the potential applications of LLMs in controlled text generation are set to expand, offering new opportunities for tailored communication across various domains.

4 Controlled Text Generation Techniques

Category	Feature	Method
Prompt Engineering	Token and Embedding Modifications	C-NLG[35]
	Controlled Output Strategies	N/A[2]
	Structured and Hierarchical Strategies	CTG[7]
	Evaluation and Constraint Satisfaction	PCAM[11]
	Refinement and Alignment	SLUTG[24]
Language Model Fine-Tuning	Control and Constraints	LiFi[1], F-LLM[44], ATGM[3]
	Syntactic Structure Guidance	ITEXP[40]
	Task and Instruction Integration	GENPET[13]
	Iterative Learning	TGLS[22]
Reinforcement Learning Approaches	Feedback and Adaptation	RSA[34], PH[45], ENLG[46], RLGF[47]
	Granular Feedback Mechanisms	PARGS[48], PMCTG[18], FPT[49], PDRCM[50], ESPT-T5[51]
	Feedback-Oriented Strategies	FAST[52]
	Divergence Minimization	GDC[53]
	Model Combination Techniques	MA[42]
Constraint-Based Methods	Optimization Techniques	CFF[54]
	Planning and Structure	GGP[55]
	Template and Constraint Techniques	TSMH[56]
	Adaptive Constraint Management	Entmax[57], NRETM[12]
Hybrid and Novel Techniques	Quantification and Sampling	SDS[58], TBS[59]
	Context Adaptation Strategies	TL[60]
	Theoretical Interventions	LiSeCo[61], GT-CTG[62]
	Content Strategy	PLANET[63]

Table 1: This table presents a comprehensive summary of controlled text generation techniques, categorized into five main methodologies: Prompt Engineering, Language Model Fine-Tuning, Reinforcement Learning Approaches, Constraint-Based Methods, and Hybrid and Novel Techniques. Each category lists specific features and associated methods, highlighting the diverse strategies employed to enhance the precision and adaptability of large language models (LLMs) in generating controlled text.

Table 3 presents a detailed comparison of different methodologies employed in controlled text generation, emphasizing their unique features and contributions to the field. The pursuit of controlled text generation is increasingly vital as language models are tasked with producing outputs that align with specific user-defined constraints. This section delves into various techniques that facilitate this control, highlighting innovative methodologies that enhance the precision and adaptability of large language models (LLMs). As illustrated in **??**, the hierarchical categorization of controlled text generation techniques encompasses five primary methodologies: Prompt Engineering, Language Model Fine-Tuning, Reinforcement Learning Approaches, Constraint-Based Methods, and Hybrid and Novel Techniques. Table 1 provides an overview of the various methodologies and techniques employed in controlled text generation, illustrating the advancements and innovations in guiding language models to produce outputs that align with specific user-defined constraints. Each of these categories is further subdivided into specific techniques and applications, along with innovations and future directions. This comprehensive overview showcases the diverse strategies and advancements that are enhancing the precision, adaptability, and efficiency of language models in generating controlled text. The following subsection emphasizes prompt engineering, a crucial technique for guiding LLMs to generate outputs that meet predetermined criteria.

4.1 Prompt Engineering

Method Name	Control Mechanisms	Optimization Techniques	Application Scenarios
N/A[2]	Semantic Role Codes	Unlikelihood Training	Contrast Set Generation
TGLS[22]	Simulated Annealing	Simulated Annealing	Low-resource Language
SLUTG[24]	Heuristic Scoring Function	Discrete Local Search	Paraphrase Generation

Table 2: This table presents a comparative analysis of various methods for controlled text generation using prompt engineering techniques. It highlights the control mechanisms, optimization techniques, and application scenarios associated with each method, providing insight into their effectiveness in refining language model outputs.

Prompt engineering is pivotal in steering LLMs toward controlled text generation, ensuring outputs align with specific user-defined criteria. This involves crafting input prompts to influence the model's output, thereby adhering to desired attributes or constraints. [2] illustrates the efficacy of generating text conditioned on structured control codes, demonstrating prompt engineering's potential in refining LLM outputs. Table 2 provides a detailed overview of different methods employed in prompt engineering for controlled text generation, emphasizing their control mechanisms, optimization techniques, and application scenarios.

In unsupervised text generation, TGLS, as introduced by [22], employs simulated annealing and a conditional generative model to frame text generation as a search problem guided by prompt engineering. Similarly, the SLUTG method by [24] uses a heuristic scoring function to iteratively refine candidate sentences, further showcasing prompt engineering's role in enhancing text generation quality.

Prompt engineering techniques involve preprocessing inputs to incorporate desired conditions, altering token embeddings, and adjusting self-attention mechanisms to guide the language model's output effectively. The hierarchical model proposed by [23] highlights the importance of structured plan extraction from corpora, emphasizing planning in prompt engineering for controlled text generation.

Prompt engineering remains crucial in advancing controlled text generation, offering innovative solutions for guiding LLMs to produce high-quality, user-aligned text across diverse applications. As NLP evolves, integrating structured control codes, heuristic scoring functions, and iterative search methods is expected to significantly enhance prompt engineering's efficacy, shifting from traditional supervised learning to more flexible, unsupervised techniques. Employing heuristic objective functions and discrete search algorithms optimizes outputs, improving performance while reducing reliance on extensive labeled datasets. Innovations in prompt engineering, informed by communication theory, facilitate a deeper understanding of effective prompting strategies, expanding NLP technologies' potential in personalized text generation and low-resource language processing [64, 65, 24].

4.2 Language Model Fine-Tuning

Fine-tuning is essential for adapting LLMs for controlled text generation, refining pretrained models on additional datasets to enhance their ability to generate text aligned with specific control parameters. The TGLS method exemplifies this by alternating between search and learning phases, effectively coupling these processes to improve text generation quality [22].

Fine-tuning incorporates auxiliary tasks, enabling content and attribute control by integrating content inputs into the generation process. This enhancement improves LLM controllability, allowing users to tailor outputs to specifications such as writing style, sentiment, and thematic consistency, ensuring generated text meets contextual and quality requirements [30, 25, 4]. Feedback-aware self-training methods can generate counterfactual examples and filter noisy data, further refining the model's control capabilities.

Moreover, fine-tuning optimizes LLM performance by integrating instructions and labeled examples, enhancing data efficiency in controlled text generation. This involves training attribute classifiers on limited labeled data to generate fine-grained control codes, labeling a larger pool of unlabeled data to enhance control over generated outputs. By employing continuous, relative, and nonexclusive control codes, the approach enables nuanced manipulation of attributes such as sentiment, topic, and writing style, ultimately improving the precision and effectiveness of generated content [66, 1].

Fine-tuning is crucial for adapting LLMs to controlled text generation, allowing models to produce outputs conforming to specific user-defined constraints and attributes. This adaptability is valuable in diverse applications, including personalized text generation, where fine-grained linguistic controls enable customization across dimensions such as sentiment, formality, and clarity. Additionally, fine-tuning enhances smaller models' performance by leveraging synthetic data generated from fine-tuned teacher LLMs, reducing the need for extensive labeled datasets. The ability to finely control text attributes and the efficiency gained through fine-tuning significantly expand LLMs' practical utility in real-world scenarios [67, 30, 68, 37]. As the field progresses, developing more efficient and targeted fine-tuning techniques will continue to enhance LLM capabilities in generating high-quality, controlled text.

4.3 Reinforcement Learning Approaches

Reinforcement learning (RL) is a pivotal approach for enhancing controlled text generation, providing a framework for models to learn optimal strategies through iterative feedback mechanisms. The integration of RL in text generation is exemplified by using web crawling and RL to produce engaging summaries, showcasing RL's potential in synthesizing coherent and user-aligned content [46]. This method leverages RL's dynamic nature to continuously refine outputs, ensuring adherence to specific user-defined goals.

The RLGF method significantly surpasses traditional RL techniques such as Proximal Policy Optimization (PPO), demonstrating the effectiveness of guided feedback in fine-tuning LLMs for specialized tasks [47]. This advancement underscores RL's capacity to enhance model adaptability and precision, aligning generated text with desired attributes and constraints.

Furthermore, the RSA-Control method introduces a self-adjustable rationality parameter, enabling dynamic control strength modulation based on contextual requirements [34]. This flexibility allows for nuanced control over text generation, adapting to varying levels of user-defined constraints and enhancing the quality of generated content.

The Prompt Highlighter approach further illustrates RL's role in controlled text generation by guiding the autoregressive generation process through adjusted attention scores [45]. This technique facilitates producing outputs that closely align with user needs, highlighting RL's adaptability in managing prompt-based interventions.

Recent advancements in RL techniques, including token-level feedback mechanisms and novel reward-shaping strategies, have demonstrated significant improvements in aligning model outputs with user-defined constraints and attributes. For instance, new approaches provide dense rewards for each generated token, resulting in a 21

4.4 Constraint-Based Methods

Constraint-based methods in controlled text generation involve applying specific rules or conditions to guide language model outputs, ensuring adherence to predefined attributes or constraints. These methods are crucial for generating high-quality and relevant content, particularly in complex applications demanding precise control over various text attributes, such as salient information tracking in data-to-text generation and addressing coherence and reasoning challenges. Advanced techniques, including tracking modules simulating human-like writing processes and unsupervised constrained generation methods, enhance content creation effectiveness across diverse contexts [5, 69, 18, 4].

The GGP (Graph-based Grouping Planner) method exemplifies explicit control in text generation by initially creating a detailed plan from key phrases before generating the final text [55]. This approach ensures that generated content aligns with the user's intended structure and thematic elements, offering a high degree of control over the output.

Another innovative approach transforms constrained text generation into a combinatorial optimization problem, as demonstrated by [54]. This method employs constraint programming to solve the optimization problem, allowing for generating text adhering to multiple, simultaneous constraints, particularly effective in scenarios where traditional methods struggle with complex constraint interactions.

COLLIE introduces a grammar-based framework that facilitates specifying rich, compositional constraints across various text generation levels [33]. This framework enhances the adaptability and precision of language models in producing text that meets specific constraints.

The Neural Rule-Execution Tracking Machine (NRETM) employs a dynamic tracking mechanism capable of managing multiple logical constraints simultaneously, distinguishing it from traditional methods [12]. This capability is crucial for applications requiring generating text with intricate logical dependencies and constraints, ensuring coherence and contextual relevance.

Entmax sampling, as proposed by [57], introduces a natively sparse probability distribution that adaptively changes the number of words considered based on context. This method enhances control over text generation by allowing nuanced adjustments to the probability distribution, ensuring generated text aligns with specific constraints.

Constraint-based methods systematically incorporate specific rules and conditions—structural, stylistic, and knowledge-intensive constraints—that effectively guide language model outputs. These methods enhance the ability to tailor generated content according to desired attributes and address generative failures by employing optimization techniques and internal model knowledge, thereby improving the overall reliability and quality of the generated text [4, 70, 71, 11]. These techniques ensure generated text meets predefined attributes and maintains high quality across diverse applications. As these methods evolve, they will contribute to advancing controlled text generation, offering innovative solutions for aligning model outputs with user-defined constraints and attributes.

4.5 Hybrid and Novel Techniques

Hybrid and novel techniques in controlled text generation represent significant advancements, combining various methodologies to enhance the precision and flexibility of language models. One innovation is the introduction of a semantic drift score, quantifying the separation between correct and incorrect facts, enabling more effective control over the generation process [58]. This approach is crucial for maintaining the factual integrity of generated content, particularly in accuracy-sensitive applications.

Another notable development combines search trees with confidence-based sampling, representing a hybrid technique for controlled text generation [59]. This method leverages the strengths of both search-based and probabilistic approaches, allowing for nuanced control over the generation process and ensuring outputs align with user-defined constraints.

LiSeCo introduces a control-theoretic intervention that guarantees steering outputs into the allowed region with minimal computational overhead [61]. This technique exemplifies integrating control theory into text generation, offering a systematic approach to managing the complex dynamics of language model outputs.

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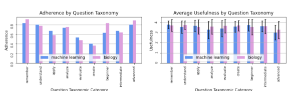
The systematic mixing of representation levels, as highlighted by [72], provides a more flexible and efficient text generation process, allowing seamless integration of various representational forms and enhancing language models' adaptability to diverse textual inputs and constraints.

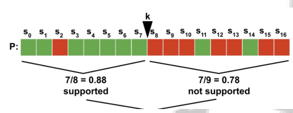
Implementing Nash equilibrium in controlled text generation optimizes the balance between directive and narrative prompts, achieving high-quality content through identifying stable strategy profiles [62]. This game-theoretic approach underscores the potential of strategic interactions in refining language models' control mechanisms.

PLANET, a novel framework that dynamically integrates content planning and surface realization in autoregressive Transformers, represents a significant advancement in hybrid techniques [63]. By combining planning and realization phases, this framework enhances the coherence and relevance of generated narratives, offering a comprehensive solution for controlled text generation.

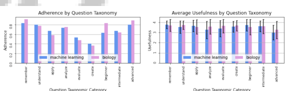
As shown in Figure 4, this figure illustrates the key hybrid and novel techniques in controlled text generation, highlighting the semantic drift score, search trees with confidence-based sampling, and control-theoretic interventions. Each method enhances precision, flexibility, and efficiency in language models. These hybrid and novel techniques highlight the ongoing evolution of controlled text generation, showcasing innovative solutions that enhance language models' precision, flexibility, and efficiency. As these techniques in controllable text generation, outline-guided writing, and knowledge-enhanced models continue to evolve, they are poised to significantly advance natural language processing. This progress will create new opportunities for customized communication across various applications, enhancing the quality and relevance of generated content by integrating structured writing strategies, diverse knowledge sources, and user-specific intentions [4, 5, 10, 69, 8].



(a) Adherence and Average Usefulness by Question Taxonomy[20]



(b) Supporting and Not Supporting a Decision[58]



(c) Adherence and Average Usefulness by Question Taxonomy[19]

Figure 3: Examples of Hybrid and Novel Techniques

The provided examples illustrate diverse approaches and the potential of these techniques in various domains. The first image highlights the comparison of adherence and average usefulness across different question taxonomic categories, specifically for machine learning and biology questions, underscoring the importance of aligning generated content with educational objectives. The second image delves into decision-making intricacies, illustrating how hybrid techniques can support or challenge decisions through segmented visual representation, emphasizing text generation's nuanced role in decision support systems. Lastly, the third image reiterates the comparative analysis of adherence and usefulness, further breaking down the data by domain-specific categories. Collectively, these examples showcase the innovative application of hybrid and novel techniques in controlled text generation, highlighting their potential to enhance educational and decision-making frameworks [20, 58, 19].

Feature	Prompt Engineering	Language Model Fine-Tuning	Reinforcement Learning Approaches
Control Mechanism	Structured Control Codes	Attribute Classifiers	Iterative Feedback Mechanisms
Optimization Technique	Heuristic Scoring Function	Feedback-aware Self-training	Token-level Feedback
Application Scenario	Unsupervised Text Generation	Personalized Text Generation	Engaging Summaries

Table 3: This table provides a comparative analysis of three primary techniques used in controlled text generation: Prompt Engineering, Language Model Fine-Tuning, and Reinforcement Learning Approaches. It highlights the distinct control mechanisms, optimization techniques, and application scenarios associated with each method, showcasing their roles in enhancing the precision and adaptability of language models.

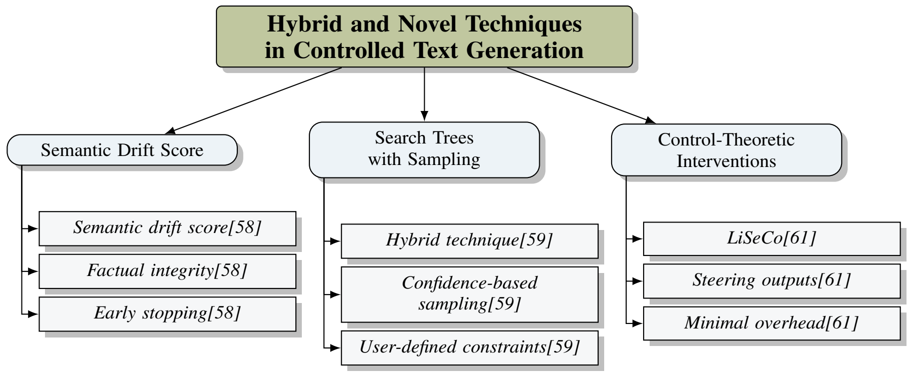


Figure 4: This figure illustrates the key hybrid and novel techniques in controlled text generation, highlighting the semantic drift score, search trees with confidence-based sampling, and control-theoretic interventions. Each method enhances precision, flexibility, and efficiency in language models.

5 Applications of Controlled Text Generation

5.1 Education

Controlled text generation (CTG) is revolutionizing education by enabling the creation of tailored content that meets pedagogical objectives and learning standards. This technology facilitates the production of educational materials that are both contextually relevant and adaptable to diverse learning preferences. For example, the GeneUS model automates user story creation in software engineering, streamlining educational content development [73].

In educational settings, managing text attributes like sentiment, formality, and toxicity is crucial for crafting engaging content. The Locate and Edit (LE) framework effectively manages sentiment control and formality transfer, ensuring content appropriateness across various educational scenarios [74]. Such capabilities are essential for creating materials that are both informative and sensitive to learners' emotional and cultural contexts.

The Affective Text Generation Model (ATGM) demonstrates CTG's adaptability in dialogue systems and therapeutic chatbots, offering personalized learning experiences in educational and mental health domains [3]. This versatility underscores CTG's role in enhancing educational resource quality and accessibility.

Datasets like COLLIE-v1, sourced from real-world data, provide a robust foundation for developing educational content that adheres to specific constraints, ensuring accuracy and relevance [33]. This approach is key to producing high-quality, contextually appropriate educational materials that cater to diverse learner needs.

CTG's integration into education offers a transformative approach to improving educational material quality and accessibility. By utilizing advanced modulation strategies and knowledge-enhanced techniques, CTG generates high-quality, tailored content, such as diverse educational questions, easing teachers' workloads while ensuring pedagogical effectiveness. Innovations in sequentially controlled text generation enable the creation of structured, coherent long-form content that closely resembles human writing, enriching the educational experience. These advancements address challenges in content generation, including bias and coherence, and hold the potential to revolutionize instructional practices and resource availability [4, 5, 75, 20, 8]. As these techniques evolve, they are poised to play a crucial role in advancing educational methodologies and improving learning outcomes, making education more personalized and effective for learners worldwide.

5.2 Healthcare

Controlled text generation holds significant promise in healthcare by generating contextually accurate and personalized content essential for patient communication, medical documentation, and decision support systems. Integrating CTG techniques into healthcare applications can enhance clinical documentation quality by ensuring adherence to specific medical guidelines, thus improving clarity and precision in patient records. Recent advancements, including sequentially controlled text generation and knowledge-enhanced models, enable greater structural awareness and integration of relevant medical knowledge, resulting in coherent, contextually appropriate outputs that address challenges like bias and interpretability prevalent in current systems [4, 5, 75, 8, 76].

A key application of CTG in healthcare is automating medical report generation. By utilizing large language models (LLMs) with advanced fine-tuning techniques, healthcare providers can produce comprehensive, precise medical reports that meet clinical protocols and enhance documentation quality. These models excel in processing unstructured data, creating reports that are complete, accurate, and verifiable, thereby addressing complex information needs. Integrating automated grammar checking further improves coherence and readability, ensuring reliability for clinical use [77, 9, 78, 21, 79].

Advancements in CTG techniques also enable the creation of personalized patient education materials tailored to individual health literacy levels and needs. By leveraging modulation strategies, these methods enhance clarity and relevance, ensuring patients receive comprehensible and actionable guidance [75, 4]. Controlling attributes such as readability and sentiment ensures that information is accessible, improving patient engagement and adherence to treatment plans.

In mental health, CTG techniques, particularly those using LLMs, enhance therapeutic chatbots and virtual assistants, providing personalized support through coherent and contextually relevant interactions. Addressing challenges like bias and interpretability, these chatbots can offer effective, tailored therapeutic experiences, improving patient outcomes [5, 75, 80, 4]. By controlling emotional tone and content, these systems provide empathetic responses, enriching the therapeutic experience.

CTG significantly enhances clinical decision support systems by generating evidence-based recommendations and alerts, assisting clinicians in making informed decisions while addressing bias and reasoning challenges in text generation. Recent advancements in causal modeling and knowledge-enhanced techniques improve the reliability of these systems by mitigating biases and integrating diverse knowledge forms, leading to better patient outcomes [81, 4, 5, 82, 8]. By integrating structured and unstructured data, CTG provides comprehensive insights that support clinical workflows and improve patient outcomes.

As illustrated in Figure 5, the implementation of CTG in healthcare can fundamentally transform various aspects of the field, improving communication clarity among professionals, enhancing documentation accuracy, and supporting informed decision-making through tailored information delivery. This figure highlights the key applications of Controlled Text Generation (CTG) in healthcare, specifically its use in medical report generation, patient education materials, and mental health chatbots, along with the specific techniques and strategies employed in each domain. By leveraging advanced techniques such as knowledge-enhanced models, CTG addresses specific healthcare communication challenges, leading to better patient outcomes and streamlined workflows [83, 5, 75, 4, 8]. As these technologies evolve, they are poised to play a crucial role in enhancing healthcare delivery and patient care.

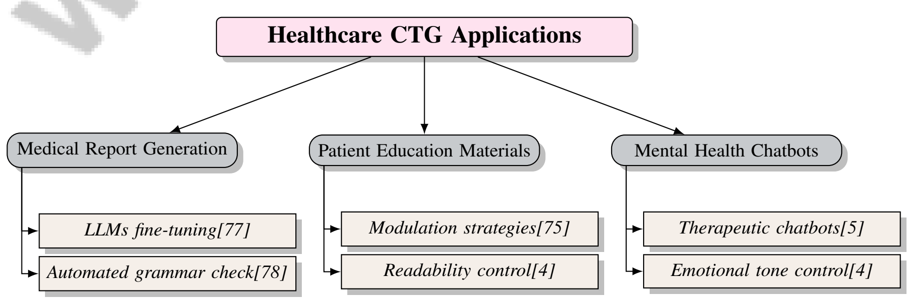


Figure 5: This figure illustrates the key applications of Controlled Text Generation (CTG) in healthcare, highlighting its use in medical report generation, patient education materials, and mental health chatbots, along with the specific techniques and strategies employed in each domain.

5.3 Content Creation and Storytelling

Controlled text generation is pivotal in content creation and storytelling, enabling the production of narratives that adhere to specific constraints while maintaining coherence and engagement. The GGP method demonstrates superior performance in generating coherent long texts compared to existing baselines, highlighting the effectiveness of structured planning in narrative generation [55].

The PHVM framework has shown practical applications in advertising text and recipe generation, showcasing the versatility of CTG in producing diverse content that meets user-defined criteria [84]. The LiFi framework introduces stylistic novel writing tasks, exemplifying CTG's potential in crafting narratives that align with specific stylistic requirements [1].

The TGLS framework is applicable in generating paraphrases and formalizing text, crucial for adapting content to different contexts and audiences [22]. The search and learning approach for unsupervised text generation achieves significant improvements over previous methods, demonstrating the potential of unsupervised techniques in generating high-quality text without extensive labeled datasets [24].

The ITEXP method enhances control over syntax and generation efficiency, making it suitable for content creation and storytelling applications [40]. Experiments in generating news headlines, meta reviews, and search ads showcase the practical applications of CTG in real-world scenarios [52].

CTG represents a transformative approach in content creation and storytelling, leveraging advanced techniques to enhance narrative construction while adhering to user-defined parameters. This method improves structural coherence and grammatical accuracy of longer texts and facilitates the generation of diverse, engaging content. By utilizing strategies such as sequential control and plug-and-play decoding, researchers impose constraints on narratives to align with desired themes or keywords. Ongoing advancements aim to mitigate biases in training data, promoting fairness and creativity in open-domain applications like storytelling and poetry, thereby paving the way for tailored and impactful storytelling experiences [75, 27, 7, 4]. As these techniques evolve, they will contribute to advancing storytelling methodologies and offer new opportunities for creative expression across diverse media.

5.4 Business Process Management

Controlled text generation has significant implications for Business Process Management (BPM), particularly in enhancing the efficiency and accuracy of information extraction from unstructured textual documents. Large Language Models (LLMs) are increasingly utilized to perform complex BPM tasks, leveraging their ability to process and generate text with high contextual relevance and coherence [77]. These models excel in mining both imperative and declarative process models, essential for understanding and optimizing business workflows by extracting structured information from text.

LLMs also play a pivotal role in assessing task suitability for robotic process automation (RPA), a critical component of modern BPM strategies. Their ability to evaluate and categorize tasks for automation streamlines RPA integration, enhancing overall process efficiency and reducing manual intervention [77]. This capability is particularly valuable in environments where automating repetitive, rule-based tasks can yield significant cost savings and productivity improvements.

The use of CTG in BPM not only enhances insight extraction from unstructured data but also facilitates the creation of intelligent systems that improve decision-making processes by leveraging LLMs' advanced reasoning capabilities. These systems can address multiple BPM-related tasks, such as mining process models from descriptions and assessing task suitability for RPA, without extensive configuration or prompt engineering [77, 75, 5, 4]. By generating insights from large volumes of textual data, LLMs contribute to informed decision-making, enabling organizations to respond swiftly to changing business conditions. As these technologies evolve, they are poised to transform BPM practices, offering innovative solutions for optimizing processes and enhancing organizational performance.

5.5 Media and Entertainment

Controlled text generation has profoundly transformed media and entertainment by providing advanced methodologies for content creation, curation, and personalization. This enables the production of coherent narratives while addressing challenges like bias and structural coherence. Innovations such as sequentially controlled text generation enhance the structural integrity and topical relevance of longer texts, while unsupervised methods allow flexible content generation without extensive supervised data, making these technologies versatile and impactful in generating creative works [4, 5, 75, 18, 7]. The ability of LLMs to generate high-quality, contextually relevant text has transformed media content production and consumption, allowing for personalized narratives and interactive experiences that engage audiences effectively.

In media, CTG facilitates the automation of news article generation, enabling rapid content production that adheres to specific editorial guidelines. This is particularly valuable for timely reporting, such as breaking news, where LLMs generate coherent, accurate articles that maintain the publication's voice and tone. CTG significantly enhances media content personalization by enabling article and recommendation customization to align with individual user preferences. Utilizing modulation strategies that adjust key text components improves structural coherence and topical relevance, boosting reader engagement and satisfaction while approaching human-level writing performance [75, 4].

The entertainment industry has also benefited from CTG, particularly in creating interactive storytelling experiences. By leveraging LLMs, creators can develop dynamic narratives that respond to user inputs, allowing personalized storylines that adapt to audience choices. This interactivity enhances immersion by empowering users with agency, a dynamic static narratives cannot replicate. Controlled and adaptive storytelling, akin to methods explored in theatrical cue generation and game-theoretic text generation, fosters deeper emotional connections and relevance, enriching user experience [85, 62].

Moreover, CTG enables the development of virtual characters and chatbots that engage users in natural, context-aware conversations, essential for immersive character development in video games and virtual environments. Integrating realistic dialogue and nuanced interactions preserves player immersion and enhances overall user experience. Employing advanced techniques like game-theoretic frameworks and CTG allows developers to manipulate language model outputs strategically, producing high-quality, contextually relevant dialogue that aligns with user intentions and emotional cues, thereby enriching narrative depth and engagement in interactive experiences [86, 85, 10, 62].

Integrating CTG into media and entertainment applications enhances content production efficiency through advanced modulation strategies, ensuring structural coherence and topical relevance while fostering innovative avenues for creative expression and interactive audience engagement. As these technologies evolve, they are poised to redefine media and entertainment boundaries, offering innovative solutions that enhance content quality and personalization across platforms.

6 Challenges and Limitations

The challenges and limitations of controlled text generation (CTG) encompass ethical, computational, and resource-related dimensions. Ethical considerations focus on biases and misuse potential, necessitating a thorough examination of responsibilities associated with deploying these technologies. Computational demands for fine-tuning large language models (LLMs) and resource constraints further complicate scalability and effectiveness. This section addresses ethical concerns surrounding bias, misuse potential, and responsible technology use, transitioning to the first subsection titled **Bias, Ethical Concerns, and Misuse Potential**.

6.1 Bias, Ethical Concerns, and Misuse Potential

CTG poses significant ethical challenges due to biases inherent in LLMs and their potential misuse. These models can amplify biases present in training data, raising concerns about reinforcing stereotypes and generating biased content [13]. The limited interpretability of deep neural networks complicates efforts to ensure quality while adhering to constraints [3]. Misuse of CTG technologies to produce harmful content is a major concern. Model arithmetic can lead to deceptive outputs, while crafting non-diegetic prompts may disrupt user experience [23]. The reliability of CTG systems is crucial; LLM-based agents may generate invalid plans, impacting user trust and highlighting ethical implications. The black-box nature of these models complicates adherence to constraints, revealing limitations in both structural and stylistic prompt adherence [87, 4, 11]. The risk of misuse underscores the necessity for robust detection systems and ethical guidelines. The evolving security landscape and lack of awareness among stakeholders further complicate these challenges, necessitating ongoing research. Automated extraction and filtering in CTG may introduce quality issues, impacting the reliability of generated content and evaluation benchmarks. Despite advancements in large-scale pre-trained language models improving diversity and fluency, insufficient oversight can result in content lacking pedagogical soundness [17, 78, 20, 18]. Addressing these concerns is critical for responsible CTG deployment. Implementing robust safeguards and enhancing awareness of risks, such as data bias and copyright issues, can help leverage CTG advantages while mitigating negative implications. This ensures that CTG advancements contribute positively to educational and societal contexts, fostering responsible technology use [88, 18, 21, 20, 8].

6.2 Computational and Resource Limitations

CTG faces significant computational and resource limitations affecting its scalability and effectiveness. A primary constraint is the substantial computational resources required for fine-tuning LLMs, which can be prohibitive in resource-constrained settings [73]. The complexity of selecting and optimizing transformation networks is crucial for maintaining representation integrity [40]. The non-deterministic nature of LLM outputs necessitates translation into formalized languages, adding to the computational burden [11]. Current methods struggle to control multiple subjects simultaneously without retraining, and while focused prefix tuning (FPT) methods improve control, they incur higher time costs [1]. The reliance on structured training data poses additional challenges, as such data may not always be accessible [22]. Manual logical forms for content selection further limit scalability, making large-scale applications impractical [73]. Token limits in text encoding hinder diffusion models, leading to omissions and inaccuracies in processing long prompts, affecting output quality [2]. Moreover, reliance on structured input data may limit generalization to complex datasets [24]. Inefficiencies in Natural Language Inference (NLI) strategies can slow down generation, particularly with multiple iterations required for checks [35]. The quality of guide policies in Reinforcement Learning with Guided Feedback (RLGF) methods may also impact performance [11]. The additional computational overhead from extra decoding branches exemplifies resource constraints in CTG [1]. Addressing these limitations is essential for advancing the field, as they hinder various modulation strategies, structural awareness in long-range text, and external knowledge integration, all critical for improving coherence and overall quality [4, 5, 75, 8, 11]. Developing more efficient models and methodologies is crucial for expanding CTG applicability across domains, ensuring it meets the growing demand for high-quality, contextually relevant text.

6.3 Control Mechanisms and Attribute Management

Implementing control mechanisms and effective attribute management in CTG presents challenges as text generation technologies become more sophisticated. While these advancements expand potential applications, they also increase the risk of harmful outcomes if control mechanisms are inadequately implemented [14]. A core challenge is generating contextually appropriate cues without extensive manual intervention, as existing methods often fall short [85]. Controlling the generation of explanations in specified formats poses another obstacle, leading to omissions and ambiguities in outputs. This highlights the need for precise control over format and content to ensure clarity and coherence [89]. The absence of fine-grained sentence-level planning can result in cascading coherence errors, particularly in complex narratives requiring deeper contextual understanding. Hierarchical structures and planning mechanisms, such as those employed in the PHVM framework, demonstrate potential for addressing these challenges by modeling input data and maintaining coherence across sentences. However, even advanced planning mechanisms may struggle with complex narratives, indicating a need for further advancements in control mechanisms and attribute management [84, 55]. The challenges of effective control mechanisms and attribute management in CTG underscore the need for ongoing research and development. Improving precision and reliability of language models is essential to meet complex real-world requirements, including safety, thematic consistency, and specific user needs, such as stylistic preferences. Recent advancements in CTG techniques—including model retraining, fine-tuning, and prompt engineering—show promise in enhancing text quality. However, issues like reduced fluency and practicality remain significant hurdles necessitating further empirical exploration and innovative solutions for achieving coherent, human-like outputs across diverse applications [75, 25, 4]. Addressing these challenges can improve the quality and coherence of generated text, aligning it with user-defined constraints and expectations.

6.4 Long Text Generation and Coherence

Generating coherent long texts with controlled attributes presents substantial challenges, particularly in maintaining narrative coherence and logical progression over extended lengths. Current models often struggle with appropriate content selection and ordering, critical for coherent long-form narratives [63]. The lack of explicit mechanisms to manage event transitions and thematic consistency can lead to disjointed outputs, undermining text quality. A primary challenge in long text generation is effectively planning event transitions, essential for ensuring logical narrative flow. The absence of such planning may result in abrupt transitions, disrupting reader engagement and comprehension [90]. Innovative approaches that explicitly arrange events within the text are necessary to enhance coherence and readability. Managing multiple attributes—such as style, tone, and factual consistency—complicates long text generation, requiring integration of diverse stylistic elements while adhering to factual accuracy. This multifaceted challenge is exacerbated by the need for LLMs to maintain smooth control over these attributes, crucial for applications like writing assistants. Recent research highlights the difficulties in achieving this balance, emphasizing the importance of effective evaluation frameworks and training methods to enhance consistency and relevance across contexts [5, 30, 86]. Models must generate content that is contextually relevant, logically ordered, and adheres to user-defined constraints throughout the text, balancing narrative coherence with attribute requirements, a task current models often find challenging. Effective generation of coherent long texts with specific controlled attributes requires significant advancements in content planning and event transition management. Recent studies reveal challenges such as structural coherence, reasoning complexity, and the need for improved evaluation metrics in text generation tasks. These advancements are vital for enhancing the quality and relevance of long-form content produced by LLMs, which currently struggle with maintaining human-like writing structures over extended narratives [5, 91, 75, 4]. Developing sophisticated models that can effectively organize and integrate diverse narrative elements will enhance the quality and coherence of long-form text generation, ensuring outputs meet user expectations and maintain thematic integrity across various applications.

7 Future Directions

Exploring future directions in controlled text generation (CTG) necessitates a focus on advancements in model architecture and training methodologies. These enhancements are vital for refining existing models and addressing current limitations within the field. The following subsections will discuss specific improvements in model architecture and training that can significantly enhance the efficacy and adaptability of CTG systems.

7.1 Enhancements in Model Architecture and Training

Advancements in model architecture and training methodologies are essential for progressing controlled text generation (CTG) and overcoming existing challenges. Future research may prioritize automating effective task description generation and improving models' contextual understanding and emotional adaptability, resulting in more sophisticated and contextually aware text generation. This evolution can enhance coherence and relevance by integrating diverse knowledge forms, addressing biases, reasoning, and interpretability issues [5, 8, 92].

Robustness improvements in models like LiFi across various tasks suggest promising architectural and training refinements [1]. Additionally, enhancing control code design and incorporating semantic representations can augment models like Tailor, enabling precise control over generated text [2].

Future work should also focus on advancing search algorithms and noise robustness, developing efficient search techniques and scoring functions. Expanding benchmarks to encompass diverse datasets and evaluation metrics will further enhance model applicability across language generation tasks [23].

By addressing critical challenges such as bias, reasoning, and interpretability, and integrating varied knowledge forms into text generation models, future research can significantly advance language technologies. This will foster the creation of sophisticated, reliable, and adaptable solutions tailored to specific applications, including summarization, translation, and question answering, ultimately improving the effectiveness of natural language processing systems in real-world contexts [5, 8].

7.2 Advanced Control Mechanisms

The development of advanced control mechanisms in controlled text generation is crucial for enhancing language models' precision and adaptability. These mechanisms enable text generation that aligns closely with user-defined constraints, improving output quality and relevance. One innovative approach is reinforcement learning, which allows models to iteratively refine outputs based on feedback, ensuring adherence to desired attributes [46]. This dynamic learning process continuously enhances generation.

Control-theoretic interventions, such as those introduced by LiSeCo, exemplify the potential of advanced control mechanisms to guide outputs effectively with minimal computational overhead [61]. This highlights the effectiveness of applying control theory principles to manage language model complexities.

Moreover, implementing Nash equilibrium strategies in text generation offers a framework for balancing directive and narrative prompts, optimizing content quality through stable strategy profiles [62]. This game-theoretic approach underscores strategic interactions' potential in refining control mechanisms, presenting new avenues for enhancing language models' precision and reliability.

Dynamic prompt adaptation, as demonstrated by the RSA-Control method, showcases advanced control mechanisms' ability to adjust control strength based on contextual needs, enhancing language models' adaptability [34]. This flexibility facilitates nuanced control over text generation, ensuring outputs meet specific user-defined constraints across diverse applications.

The evolution of advanced control mechanisms signifies a substantial advancement in controlled text generation, offering innovative solutions for aligning model outputs with user-defined constraints. As these mechanisms develop, they are poised to significantly enhance language technologies by integrating modulation strategies, knowledge incorporation, and structured generation techniques. This evolution will yield more sophisticated and reliable solutions for generating high-quality controlled text, as evidenced by recent research focused on sequentially controlled text generation and knowledge-enhanced models, which aim to improve coherence, grammaticality, and alignment with user intentions in practical applications. Furthermore, ongoing exploration of diverse architectures and evaluation methodologies will deepen understanding of their strengths and utility, ultimately advancing text generation capabilities across various domains [4, 5, 75, 10, 8].

7.3 Applications and Domain-Specific Adaptations

Future research in controlled text generation is poised to explore a wide range of applications and domain-specific adaptations, enhancing language models' versatility and effectiveness across various fields. In education, integrating generated questions into classroom settings and comparing their efficacy to human-generated questions could refine pedagogical approaches [80]. Extending frameworks like STANDARDIZE to other languages and contexts could provide more inclusive learning tools.

Exploring multilingual generation using universal POS tags presents promising opportunities for real-world data-to-text applications, potentially bridging language gaps in diverse educational and professional settings. Integrating benchmarks for a wider array of languages, alongside exploring non-causal models like Masked Language Modeling (MLM) in various natural language generation (NLG) tasks, can significantly enhance language models' flexibility and resilience. This approach can address common challenges identified in recent literature, such as bias, coherence, and interpretability, while leveraging advanced models that outperform traditional Causal Language Modeling (CLM) in generating coherent and contextually relevant text [5, 93].

In terms of societal impact, future research could utilize frameworks like NADO to systematically identify and mitigate societal biases in generated text, fostering equitable and unbiased content generation practices. This is crucial given the challenges highlighted in recent literature, including the amplification of social biases by language models and the need for improved evaluation metrics. Addressing these issues can enhance creativity and fairness in text generation, ensuring outputs align

AI-generated, for reference only.

more closely with diverse social norms and values [5, 8, 7]. Refining referring expression generation and developing robust methods for handling unseen entities and relations could further improve text generation systems' quality and efficiency, particularly in complex domains.

In business process management (BPM), future research should investigate applying large language models (LLMs) to various BPM tasks and improving prompt designs to enhance output quality [77]. Additionally, extending methods like MAGIC to modalities beyond images, such as audio and video, could enhance multimodal text generation capabilities [94].

Expanding text generation libraries with more tasks and enhancing training process efficiency are critical areas for future exploration, broadening language models' applicability in diverse domains. Integrating structured frameworks in cross-lingual contexts, alongside improving citation intents' informativeness, can significantly advance academic writing and research. Leveraging LLMs to guide the writing process through explicit outlines, as demonstrated in the Writing Path framework, can help scholars produce goal-oriented and high-quality texts that reflect user intentions. Additionally, systematically exploring citation text generation, addressing task definition and evaluation metrics challenges, can lead to more effective scholarly communications. These advancements facilitate collaboration and creativity in writing, improving overall clarity and depth in academic discourse, ultimately fostering more insightful scholarly interactions [10, 37, 4].

By exploring these future directions in controlled text generation research, we can significantly enhance the evolution of language technologies. This advancement will lead to the development of sophisticated, reliable, and adaptable solutions tailored to meet specific constraints across various applications. Integrating diverse modulation strategies and leveraging transformer-based pre-trained language models can improve controllability, structural coherence, and overall quality of generated text, facilitating effective implementations in real-world scenarios [17, 75, 4].

7.4 Ethical and Societal Implications

Advancements in controlled text generation (CTG) raise significant ethical and societal implications that require careful consideration and proactive measures. A primary concern is the potential for CTG models to perpetuate or exacerbate existing biases, leading to harmful or discriminatory content. Robust model development and bias detection mechanisms are essential to mitigate these risks and ensure generated text aligns with ethical standards [21].

Privacy-preserving practices are critical in deploying CTG systems, especially given the sensitive nature of data processed by these models. Compliance with regulatory standards is essential to protect user privacy and maintain trust in the technology. Developing parameter-efficient models can further mitigate risks by reducing computational footprints and potential exposure of sensitive information [21].

The societal implications of CTG extend to potential misuse, such as generating misleading or deceptive content. The rapid advancements in controllable text generation emphasize the urgent need for comprehensive regulatory frameworks addressing ethical considerations in its application. Such frameworks are essential to ensure that innovations in CTG enhance natural language processing capabilities while promoting societal well-being by mitigating challenges related to bias, privacy, and misuse, as highlighted in recent literature [5, 8, 18, 4]. Integrating ethical guidelines and transparency in model development can help address these concerns, fostering responsible use and public trust.

The ethical and societal implications of advancements in CTG require ongoing attention and action from researchers, developers, and policymakers. By emphasizing ethical considerations and establishing comprehensive safeguards, it is feasible to leverage the advantages of constrained text generation (CTG) technologies while effectively mitigating associated risks such as data bias, privacy violations, and the potential for misuse in generating deceptive content. This approach ensures that these advanced systems enhance natural language processing capabilities while aligning with societal values, ultimately serving the greater good [32, 21, 18].

8 Conclusion

Controlled text generation (CTG) represents a significant leap forward in natural language processing (NLP), with transformer-based pre-trained language models (PLMs) playing a pivotal role in enhancing these capabilities. While progress has been made, challenges remain in achieving precise control and maintaining output quality. Techniques such as SCTG have shown promise in improving structural coherence and text quality, nearing human-level performance, which underscores the potential of innovative approaches to advance CTG. The effectiveness of CriticControl across various tasks highlights the necessity of refining CTG methods to ensure coherent and controlled text outputs. The architecture of PLMs is fundamental to optimizing text generation, necessitating further exploration to enhance their effectiveness. Although large language models (LLMs) demonstrate proficiency in generating rationales and adhering to broad control signals, they face difficulties with strict constraints. Establishing robust evaluation frameworks that integrate human judgment with automated metrics is crucial for improving the reliability of CTG assessments. As the field progresses, the development of more advanced models and evaluation strategies will be vital in overcoming current limitations and broadening CTG capabilities, ensuring its continued positive impact on NLP.

References

[1] Chufan Shi, Deng Cai, and Yujiu Yang. Lifi: lightweight controlled text generation with fine-grained control codes. *arXiv preprint arXiv:2402.06930*, 2024.

[2] Alexis Ross, Tongshuang Wu, Hao Peng, Matthew E. Peters, and Matt Gardner. Tailor: Generating and perturbing text with semantic controls, 2022.

[3] Ishika Singh, Ahsan Barkati, Tushar Goswamy, and Ashutosh Modi. Adapting a language model for controlled affective text generation, 2020.

[4] Arnav Goel, Medha Hira, Avinash Anand, Siddhesh Bangar, and Rajiv Ratn Shah. Advancements in scientific controllable text generation methods, 2023.

[5] Jonas Becker, Jan Philip Wahle, Bela Gipp, and Terry Ruas. Text generation: A systematic literature review of tasks, evaluation, and challenges, 2024.

[6] Tian Lan, Deng Cai, Yan Wang, Heyan Huang, and Xian-Ling Mao. Copy is all you need, 2023.

[7] Nanyun Peng. Controllable text generation for open-domain creativity and fairness, 2022.

[8] Wenhao Yu, Chenguang Zhu, Zaitang Li, Zhiting Hu, Qingyun Wang, Heng Ji, and Meng Jiang. A survey of knowledge-enhanced text generation, 2022.

[9] Jasper Hawthorne, Felicity Radcliffe, and Lachlan Whitaker. Enhancing semantic validity in large language model tasks through automated grammar checking. 2024.

[10] Yukyung Lee, Soonwon Ka, Bokyung Son, Pilsung Kang, and Jaewook Kang. Navigating the path of writing: Outline-guided text generation with large language models, 2024.

[11] Albert Lu, Hongxin Zhang, Yanzhe Zhang, Xuezhi Wang, and Diyi Yang. Bounding the capabilities of large language models in open text generation with prompt constraints. *arXiv preprint arXiv:2302.09185*, 2023.

[12] Yufei Wang, Can Xu, Huang Hu, Chongyang Tao, Stephen Wan, Mark Dras, Mark Johnson, and Daxin Jiang. Neural rule-execution tracking machine for transformer-based text generation, 2021.

[13] Timo Schick and Hinrich Schütze. Few-shot text generation with pattern-exploiting training, 2021.

[14] Joseph Bullock and Miguel Luengo-Oroz. Automated speech generation from un general assembly statements: Mapping risks in ai generated texts, 2019.

[15] Zhiruo Wang, Zhoujun Cheng, Hao Zhu, Daniel Fried, and Graham Neubig. What are tools anyway? a survey from the language model perspective, 2024.

[16] Xin Liu, Muhammad Khalifa, and Lu Wang. Bolt: Fast energy-based controlled text generation with tunable biases, 2023.

[17] Hanqing Zhang, Haolin Song, Shaoyu Li, Ming Zhou, and Dawei Song. A survey of controllable text generation using transformer-based pre-trained language models, 2023.

[18] Yingwen Fu, Wenjie Ou, Zhou Yu, and Yue Lin. Effective unsupervised constrained text generation based on perturbed masking, 2024.

[19] Sabina Elkins, Ekaterina Kochmar, Iulian Serban, and Jackie CK Cheung. How useful are educational questions generated by large language models? In *International Conference on Artificial Intelligence in Education*, pages 536–542. Springer, 2023.

[20] Sabina Elkins, Ekaterina Kochmar, Jackie C. K. Cheung, and Iulian Serban. How useful are educational questions generated by large language models?, 2023.

[21] Md Nazmus Sakib, Md Athikul Islam, Royal Pathak, and Md Mashrur Arifin. Risks, causes, and mitigations of widespread deployments of large language models (llms): A survey, 2024.

[22] Jingjing Li, Zichao Li, Lili Mou, Xin Jiang, Michael R. Lyu, and Irwin King. Unsupervised text generation by learning from search, 2020.

[23] An Nguyen. Language model evaluation in open-ended text generation, 2021.

[24] Lili Mou. Search and learning for unsupervised text generation, 2023.

[25] Xun Liang, Hanyu Wang, Yezhaohui Wang, Shichao Song, Jiawei Yang, Simin Niu, Jie Hu, Dan Liu, Shunyu Yao, Feiyu Xiong, and Zhiyu Li. Controllable text generation for large language models: A survey, 2024.

[26] Iñigo Alonso and Eneko Agirre. Automatic logical forms improve fidelity in table-to-text generation, 2024.

[27] Damian Pascual, Beni Egressy, Clara Meister, Ryan Cotterell, and Roger Wattenhofer. A plug-and-play method for controlled text generation, 2021.

[28] Terrance Liu and Zhiwei Steven Wu. Multi-group uncertainty quantification for long-form text generation, 2024.

[29] Stephan Busemann and Helmut Horacek. A flexible shallow approach to text generation, 1998.

[30] Shang Zhou, Feng Yao, Chengyu Dong, Zihan Wang, and Jingbo Shang. Evaluating the smooth control of attribute intensity in text generation with llms. *arXiv preprint arXiv:2406.04460*, 2024.

[31] Yinhong Liu, Yixuan Su, Ehsan Shareghi, and Nigel Collier. Instruct-sctg: Guiding sequential controlled text generation through instructions, 2023.

[32] Keenan Jones, Enes Altuncu, Virginia N. L. Franqueira, Yichao Wang, and Shujun Li. A comprehensive survey of natural language generation advances from the perspective of digital deception, 2022.

[33] Shunyu Yao, Howard Chen, Austin W. Hanjie, Runzhe Yang, and Karthik Narasimhan. Collie: Systematic construction of constrained text generation tasks, 2023.

[34] Yifan Wang and Vera Demberg. Rsa-control: A pragmatics-grounded lightweight controllable text generation framework, 2024.

[35] Fan-Keng Sun and Cheng-I Lai. Conditioned natural language generation using only unconditioned language model: An exploration, 2020.

[36] Aman Bhargava, Cameron Witkowski, Shi-Zhuo Looi, and Matt Thomson. What's the magic word? a control theory of llm prompting. *arXiv preprint arXiv:2310.04444*, 2023.

[37] Furkan Şahinuç, Ilia Kuznetsov, Yufang Hou, and Iryna Gurevych. Systematic task exploration with llms: A study in citation text generation, 2024.

[38] Zhen Tao, Yanfang Chen, Dinghao Xi, Zhiyu Li, and Wei Xu. Towards reliable detection of llm-generated texts: A comprehensive evaluation framework with cudrt, 2024.

[39] Yi Tay, Dara Bahri, Che Zheng, Clifford Brunk, Donald Metzler, and Andrew Tomkins. Reverse engineering configurations of neural text generation models, 2020.

[40] Noe Casas, José A. R. Fonollosa, and Marta R. Costa-jussà. Syntax-driven iterative expansion language models for controllable text generation, 2020.

[41] Tianyi Tang, Junyi Li, Zhipeng Chen, Yiwen Hu, Zhuohao Yu, Wenxun Dai, Zican Dong, Xiaoxue Cheng, Yuhao Wang, Wayne Xin Zhao, Jian-Yun Nie, and Ji-Rong Wen. Textbox 2.0: A text generation library with pre-trained language models, 2022.

[42] Jasper Dekoninck, Marc Fischer, Luca Beurer-Kellner, and Martin Vechev. Controlled text generation via language model arithmetic, 2024.

[43] M. Onat Topal, Anil Bas, and Imke van Heerden. Exploring transformers in natural language generation: Gpt, bert, and xlnet, 2021.

[44] Zelong Li, Wenyue Hua, Hao Wang, He Zhu, and Yongfeng Zhang. Formal-llm: Integrating formal language and natural language for controllable llm-based agents. *arXiv preprint arXiv:2402.00798*, 2024.

[45] Yuechen Zhang, Shengju Qian, Bohao Peng, Shu Liu, and Jiaya Jia. Prompt highlighter: Interactive control for multi-modal llms, 2024.

[46] Zhi-Xuan Tai and Po-Chuan Chen. Empowering nlg: Offline reinforcement learning for informal summarization in online domains, 2023.

[47] Jonathan D Chang, Kiante Brantley, Rajkumar Ramamurthy, Dipendra Misra, and Wen Sun. Learning to generate better than your llm. *arXiv preprint arXiv:2306.11816*, 2023.

[48] Ahmad Rashid, Ruotian Wu, Julia Grosse, Agustinus Kristiadi, and Pascal Poupart. A critical look at tokenwise reward-guided text generation, 2024.

[49] Congda Ma, Tianyu Zhao, Makoto Shing, Kei Sawada, and Manabu Okumura. Focused prefix tuning for controllable text generation, 2023.

[50] Joshua Zingale and Jugal Kalita. Language model sentence completion with a parser-driven rhetorical control method, 2024.

[51] Damith Chamalke Senadeera and Julia Ive. Controlled text generation using t5 based encoder-decoder soft prompt tuning and analysis of the utility of generated text in ai, 2022.

[52] Junyi Chai, Reid Pryzant, Victor Ye Dong, Konstantin Golobokov, Chenguang Zhu, and Yi Liu. Fast: Improving controllability for text generation with feedback aware self-training, 2022.

[53] Muhammad Khalifa, Hady Elsahar, and Marc Dymetman. A distributional approach to controlled text generation, 2021.

[54] Alexandre Bonlarron and Jean-Charles Régin. Intertwining cp and nlp: The generation of unreasonably constrained sentences, 2024.

[55] Xuming Lin, Shaobo Cui, Zhongzhou Zhao, Wei Zhou, Ji Zhang, and Haiqing Chen. Ggp: A graph-based grouping planner for explicit control of long text generation, 2021.

[56] Maosen Zhang, Nan Jiang, Lei Li, and Yexiang Xue. Language generation via combinatorial constraint satisfaction: A tree search enhanced monte-carlo approach, 2020.

[57] Pedro Henrique Martins, Zita Marinho, and André F. T. Martins. Sparse text generation, 2020.

[58] Ava Spataru, Eric Hambro, Elena Voita, and Nicola Cancedda. Know when to stop: A study of semantic drift in text generation, 2024.

[59] Dylan Wilson. Llm tree search, 2024.

[60] Y. Wang, D. Ma, and D. Cai. With greater text comes greater necessity: Inference-time training helps long text generation, 2024.

[61] Emily Cheng, Marco Baroni, and Carmen Amo Alonso. Linearly controlled language generation with performative guarantees, 2024.

[62] Daniel Sefeni, Michael Johnson, and Joshua Lee. Game-theoretic approaches for stepwise controllable text generation in large language models. 2024.

[63] Zhe Hu, Hou Pong Chan, Jiachen Liu, Xinyan Xiao, Hua Wu, and Lifu Huang. Planet: Dynamic content planning in autoregressive transformers for long-form text generation, 2022.

[64] Cheng Li, Mingyang Zhang, Qiaozhu Mei, Weize Kong, and Michael Bendersky. Learning to rewrite prompts for personalized text generation, 2024.

[65] Yuanfeng Song, Yuanqin He, Xuefang Zhao, Hanlin Gu, Di Jiang, Haijun Yang, Lixin Fan, and Qiang Yang. A communication theory perspective on prompting engineering methods for large language models, 2023.

AI-generated, for reference only.

[66] Chufan Shi, Deng Cai, and Yujiu Yang. Lifi: Lightweight controlled text generation with fine-grained control codes, 2024.

[67] Jean Kaddour and Qi Liu. Synthetic data generation in low-resource settings via fine-tuning of large language models, 2024.

[68] Bashar Alhafni, Vivek Kulkarni, Dhruv Kumar, and Vipul Raheja. Personalized text generation with fine-grained linguistic control, 2024.

[69] Hayate Iso, Yui Uehara, Tatsuya Ishigaki, Hiroshi Noji, Eiji Aramaki, Ichiro Kobayashi, Yusuke Miyao, Naoaki Okazaki, and Hiroya Takamura. Learning to select, track, and generate for data-to-text, 2019.

[70] Howard Chen, Huihan Li, Danqi Chen, and Karthik Narasimhan. Controllable text generation with language constraints, 2022.

[71] Sachin Kumar, Eric Malmi, Aliaksei Severyn, and Yulia Tsvetkov. Controlled text generation as continuous optimization with multiple constraints, 2021.

[72] Emanuele Pianta and Lucia M. Tovena. Mixing representation levels: The hybrid approach to automatic text generation, 1999.

[73] Tajmilur Rahman and Yuecai Zhu. Automated user story generation with test case specification using large language model, 2024.

[74] Hye Ryung Son and Jay-Yoon Lee. Locateedit: Energy-based text editing for efficient, flexible, and faithful controlled text generation, 2024.

[75] Alexander Spangher, Xinyu Hua, Yao Ming, and Nanyun Peng. Sequentially controlled text generation, 2023.

[76] Eric Malmi, Yue Dong, Jonathan Mallinson, Aleksandr Chuklin, Jakub Adamek, Daniil Mirylenka, Felix Stahlberg, Sebastian Krause, Shankar Kumar, and Aliaksei Severyn. Text generation with text-editing models, 2022.

[77] Michael Grohs, Luka Abb, Nourhan Elsayed, and Jana-Rebecca Rehse. Large language models can accomplish business process management tasks, 2023.

[78] James Mayfield, Eugene Yang, Dawn Lawrie, Sean MacAvaney, Paul McNamee, Douglas W. Oard, Luca Soldaini, Ian Soboroff, Orion Weller, Efsun Kayi, Kate Sanders, Marc Mason, and Noah Hibbler. On the evaluation of machine-generated reports, 2024.

[79] Shaina Raza, Oluwanifemi Bamgbose, Shardul Ghuge, Fatemeh Tavakol, Deepak John Reji, and Syed Raza Bashir. Developing safe and responsible large language model : Can we balance bias reduction and language understanding in large language models?, 2025.

[80] Nikolaos Malandrakis, Minmin Shen, Anuj Goyal, Shuyang Gao, Abhishek Sethi, and Angeliki Metallinou. Controlled text generation for data augmentation in intelligent artificial agents, 2019.

[81] Carolina Zheng, Claudia Shi, Keyon Vafa, Amir Feder, and David M. Blei. An invariant learning characterization of controlled text generation, 2023.

[82] Zhiting Hu and Li Erran Li. A causal lens for controllable text generation, 2022.

[83] Vaibhav Kumar, Hana Koorehdavoudi, Masud Moshtaghi, Amita Misra, Ankit Chadha, and Emilio Ferrara. Controlled text generation with hidden representation transformations, 2023.

[84] Zhihong Shao, Minlie Huang, Jiangtao Wen, Wenfei Xu, and Xiaoyan Zhu. Long and diverse text generation with planning-based hierarchical variational model, 2019.

[85] Alara Dirik, Hilal Donmez, and Pinar Yanardag. Controlled cue generation for play scripts, 2021.

[86] Aleem Khan, Andrew Wang, Sophia Hager, and Nicholas Andrews. Learning to generate text in arbitrary writing styles, 2024.

[87] Amrita Bhattacharjee, Raha Moraffah, Joshua Garland, and Huan Liu. Zero-shot llm-guided counterfactual generation for text. *arXiv preprint arXiv:2405.04793*, 2024.

[88] Shulin Huang, Shirong Ma, Yinghui Li, Yangning Li, Shiyang Lin, Hai-Tao Zheng, and Ying Shen. Towards attribute-entangled controllable text generation: A pilot study of blessing generation, 2022.

[89] Masahiro Kaneko and Naoaki Okazaki. Controlled generation with prompt insertion for natural language explanations in grammatical error correction. *arXiv preprint arXiv:2309.11439*, 2023.

[90] Qintong Li, Piji Li, Wei Bi, Zhaochun Ren, Yuxuan Lai, and Lingpeng Kong. Event transition planning for open-ended text generation, 2022.

[91] Yi Liang, You Wu, Honglei Zhuang, Li Chen, Jiaming Shen, Yiling Jia, Zhen Qin, Sumit Sanghai, Xuanhui Wang, Carl Yang, and Michael Bendersky. Integrating planning into single-turn long-form text generation, 2024.

[92] James Shaw. Conciseness through aggregation in text generation, 1995.

[93] Nicolo Micheletti, Samuel Belkadi, Lifeng Han, and Goran Nenadic. Exploration of masked and causal language modelling for text generation, 2024.

[94] Yixuan Su, Tian Lan, Yahui Liu, Fangyu Liu, Dani Yogatama, Yan Wang, Lingpeng Kong, and Nigel Collier. Language models can see: Plugging visual controls in text generation, 2022.

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