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 represents a significant advancement in natural language processing (NLP), focusing on the ability to produce text that adheres to specific constraints or user-defined attributes. This capability is crucial for applications requiring tailored communication, as it enhances user experience and satisfaction. The demand for more precise control mechanisms in text generation underscores its importance and impact in NLP [1]. By guiding the outputs of large language models (LLMs), controlled text generation addresses inefficiencies and limitations of existing autoregressive models, which often result in suboptimal syntactic structures and reduced diversity [2].

The significance of controlled text generation lies in its dual 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 specific user intentions, which is particularly important in scenarios requiring the customization of attributes such as sentiment and readability [3]. Furthermore, controlled text generation is essential for producing emotionally nuanced text while maintaining grammatical integrity, thereby enhancing the overall quality and impact of the generated content.

Controlled text generation also plays a critical role in mitigating the potential misuse of NLP systems, such as the creation of deceptive content like fake news and misinformation. "Controlled text generation improves the reliability and relevance of outputs by implementing specific rules and constraints, which are structured through various modulation strategies that enhance the coherence, grammatical accuracy, and topical alignment of the generated content. Recent advancements have led to the development of novel tasks, such as sequentially controlled text generation, which focus on

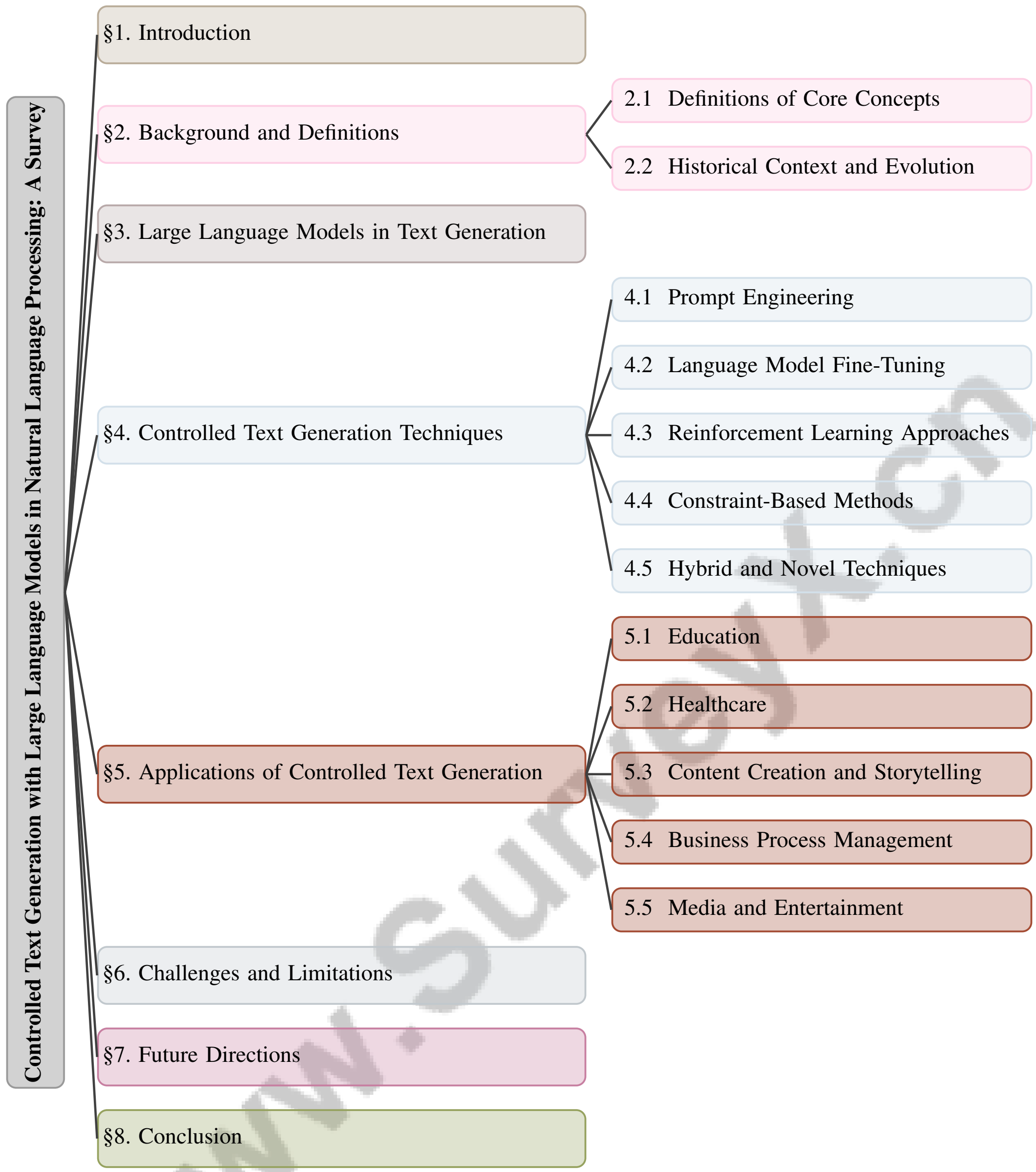

Figure 1: chapter structure

maintaining a human-like writing structure over longer documents. This approach not only increases the control accuracy but also elevates the overall quality of the text, bringing it closer to human-level performance." [4, 5]. Additionally, it addresses challenges in enhancing creativity and fairness in open-domain text generation, particularly in maintaining long-term coherence and reducing social biases.

As the demand for personalized and context-aware communication continues to grow across various domains, controlled text generation remains a key area of research and development. The integration of structured frameworks, such as the Writing Path, into Natural Language Processing (NLP) systems significantly enhances their ability to generate high-quality, goal-oriented text that aligns closely with specific user requirements. This advancement not only improves the coherence and contextual accuracy of generated outputs but also addresses common challenges in text generation, such as bias and hallucinations. By leveraging explicit outlines and knowledge-enhanced techniques, these systems are better equipped to navigate the complexities of user intentions, thereby reinforcing their critical role in the rapidly evolving landscape of language technologies. [6, 7, 8, 9]

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

Large Language Models (LLMs) have become integral to the advancement of controlled text generation, largely due to their capacity to transform structured inputs into coherent, contextually relevant narratives. These models, particularly those based on transformer architectures such as GPT-2 and GPT-3, exemplify the potential of LLMs in producing fluent and contextually accurate text [10]. The hierarchical generation framework proposed by [11] highlights 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 demonstrated by the introduction of 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 the generated content, an essential 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 the context of emotional and semantic control, the Affective Text Generation Model (ATGM) adapts the GPT-2 architecture to allow users to control both the category and intensity of emotion in the generated text [3]. This demonstrates the flexibility of LLMs in adapting to user-defined attributes, which is vital for producing emotionally nuanced content. Additionally, Tailor, a semantically-controlled text generation system, utilizes 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 [10]. To address these challenges, lightweight frameworks such as LiFi, which uses fine-grained control codes, have been proposed to enhance the controllability of LLMs without extensive computational resources [1]. These advancements highlight the ongoing evolution of LLMs in controlled text generation, emphasizing their significance in enabling the production of high-quality, user-aligned text with specified attributes.

1.3 Objectives of the Survey

The primary objectives of this survey are to provide a comprehensive overview of controlled text generation (CTG) and its applications, with a particular focus on the role of large language models (LLMs) in this process. By systematically reviewing the current state of CTG, this survey aims to address existing knowledge gaps and provide insights into various text generation tasks and their associated challenges [6]. Additionally, the survey seeks to highlight the implications of AI-generated text on human rights and political stability, underscoring the need for increased awareness of potential risks [14].

Another key goal of this survey is to examine 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 aims to introduce 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 provide a deeper 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 a particular emphasis on the role of large language models (LLMs). The paper is organized into several key sections, beginning with an introduction that establishes the significance and objectives of CTG, followed by a detailed background section that defines core concepts and traces their historical evolution. The subsequent section delves into the architecture, capabilities, and limitations of LLMs, highlighting significant advancements that have influenced text generation.

Following this foundational overview, the survey examines 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,

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providing a comprehensive understanding of the methodologies used to guide LLMs in producing text with specific attributes or constraints.

The practical applications of controllable text generation (CTG) are explored across various sectors, including education—where it can enhance question generation for teachers and improve student engagement—healthcare, content creation, business process management, and media and entertainment, demonstrating its versatility and transformative potential in improving efficiency and quality in these diverse fields. [6, 18]. This exploration underscores the versatility and impact of CTG across different fields.

The survey also addresses the challenges and limitations associated with CTG, including ethical concerns, computational constraints, and the difficulties of maintaining text quality while enforcing constraints. Revised Sentence: "Engaging in these discussions is essential for identifying and addressing the current challenges hindering the effective implementation of Constrained Text Generation (CTG) techniques, particularly in light of the common barriers such as data bias, lack of comprehensive datasets, and issues related to transparency and interpretability highlighted in recent literature." [6, 19, 20]

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 a critical area in natural language processing (NLP), focusing on creating text that meets specific constraints or attributes, such as sentiment, style, or factual accuracy [1]. This method offers precision over traditional text generation, aligning generated text with semantic, syntactic, or stylistic guidelines, essential for applications requiring varied readability tailored to diverse educational backgrounds [3]. Large language models (LLMs) like GPT-3 and BERT play a pivotal role in CTG, enabling coherent text generation across various NLP tasks, including summarization and translation [12]. However, challenges such as divergence from training data distributions necessitate integrating structured and unstructured knowledge bases to enhance adaptability to diverse linguistic inputs [2].

Core concepts in CTG include faithfulness, factual consistency, and Natural Language Generation (NLG), crucial for ensuring content accuracy and reliability [13]. Emotion-conditioned text generation is significant, leveraging extensive datasets and computational power for nuanced emotional tone control [3]. Prompt engineering, employing techniques like prompt template engineering and multi-turn prompting, is vital for refining text generation, especially in low-resource settings [21]. CTG also involves guiding outputs to avoid undesirable content while maintaining text quality [10].

Controlled table-to-text generation transforms tabular data into textual narratives, guided by user input, and is essential for understanding CTG's role in contexts like political discourse [2]. The capacity to produce controlled, high-quality text across domains underscores CTG's significance in advancing NLP technologies, ensuring alignment with user-defined constraints [1]. Definitions extend to internal and external knowledge enhancements, such as topics, keywords, and knowledge graphs, addressing challenges like generating concise text from similar messages without losing coherence [22]. CTG also includes generating coherent and diverse long texts from structured data, crucial for applications like product descriptions and recipe generation [23]. This involves creating coherent stories from key facts while maintaining adherence to those facts [21]. Furthermore, CTG enables generative models to produce text in multiple styles, overcoming limitations of models generating text in a fixed style [23]. The inefficiency and inflexibility of existing NLG methods, reliant on complex linguistic components or rigid templates, highlight the need for adaptable CTG approaches [22].

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2.2 Historical Context and Evolution

The evolution of controlled text generation (CTG) and large language models (LLMs) is closely linked with the broader development of natural language processing (NLP) and deep learning, particularly transformer-based models [17]. Early CTG methods, dominated by rule-based and template-based approaches, offered limited flexibility for complex linguistic tasks due to their reliance on manually crafted logical forms and templates, which were costly and impractical for dynamic applications [22, 24]. The introduction of Long Short-Term Memory (LSTM) networks marked progress by improving context retention over longer sequences, but the Transformer architecture revolutionized the field by modeling dependencies between words regardless of position, forming the basis for powerful LLMs like BERT and GPT [17].

The shift to pretrained language models (PLMs) enhanced contextually relevant and coherent text generation across various applications. Despite these advancements, the probabilistic nature of these models posed challenges in controlling text to include specific words or attributes, underscoring the need for innovative control mechanisms [25]. The emergence of LLMs raised concerns about factual errors and hallucinations, prompting the development of methods to quantify uncertainty in outputs [26].

CTG methods have evolved to include training-stage approaches like retraining and fine-tuning, and inference-stage techniques such as prompt engineering and latent space manipulation [23]. Traditional NLP approaches often struggled with expressiveness and constraint satisfaction, leading to a recognition of the need for comprehensive methods integrating multiple controllability aspects [4]. The historical context of CTG also involves the evolution of evaluation methods for NLG systems, challenged by differences between domain-oriented and linguistically motivated ontologies [27]. Traditional methods often lacked the ability to modulate specific attributes' intensity, leading to ineffective responses [28], and faced difficulties scaling with data size, causing bottlenecks in data retrieval and processing [29].

Recent years have seen a shift towards more efficient and adaptable approaches, driven by the need to overcome early methods' limitations and embrace new challenges. The historical context of NLG has also evolved concerning digital deception and detecting deceptive practices [30]. Existing benchmarks for constrained text generation often focus on fixed constraint types, which state-of-the-art models like GPT-4 handle with relative ease [31]. The ongoing evolution of CTG and LLMs is 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 various domains [32].

3 Large Language Models in Text Generation

In text generation, Large Language Models (LLMs) have become pivotal, driven by their sophisticated architectures and capabilities. This section examines the structural intricacies and innovative methodologies that enhance the performance of these models. Figure 2 illustrates the hierarchical structure of LLMs in text generation, focusing on their architecture and capabilities, limitations, and recent advancements. This figure categorizes the fundamental components and methodologies that enhance LLM performance, identifies existing constraints, and highlights innovative breakthroughs that are shaping the future of text generation. The following subsection will provide a detailed exploration of LLMs' architectural features and operational capacities, elucidating their role in generating coherent and contextually relevant narratives.

3.1 Architecture and Capabilities of LLMs

LLMs have revolutionized text generation through complex architectures, primarily utilizing the Transformer model's self-attention mechanism to capture intricate text dependencies. This underpins models like GPT-2, GPT-3, and BERT, facilitating coherent narrative generation via autoregressive and bidirectional context representations [33]. Dynamic prompts, such as CONTROL PREFIXES, enhance these models by integrating minimal additional parameters to tailor outputs to specific attributes [1].

The architecture of LLMs incorporates diverse methodologies, including the Neural Rule-Execution Tracking Machine (NRETM), which integrates with transformer-based text generators using predicate

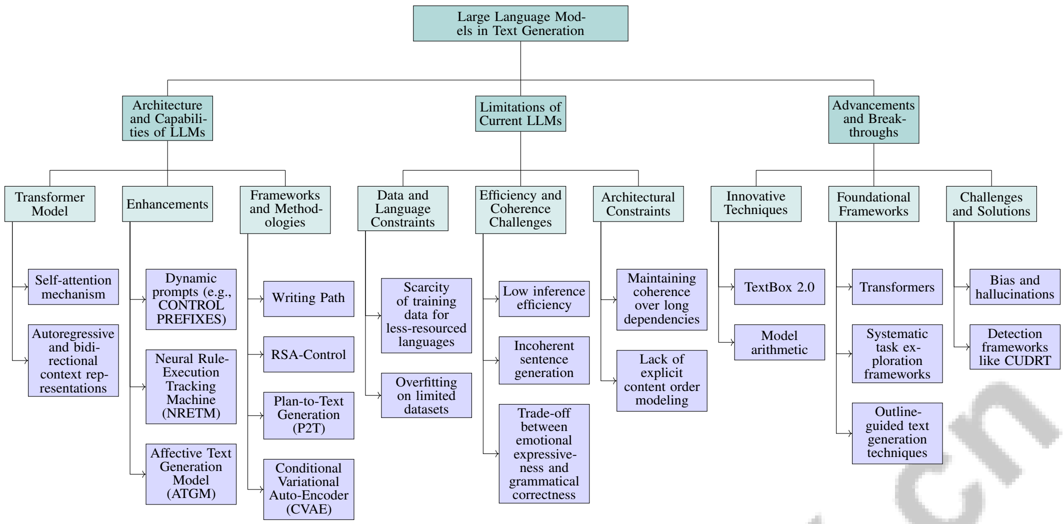

Figure 2: This figure illustrates the hierarchical structure of Large Language Models (LLMs) in text generation, focusing on their architecture and capabilities, limitations, and recent advancements. It categorizes the fundamental components and methodologies enhancing LLM performance, identifies existing constraints, and highlights innovative breakthroughs that are shaping the future of text generation.

logic to guide the process [12]. The Affective Text Generation Model (ATGM) uses a perturbation mechanism for emotion and grammaticality optimization, allowing fine-grained emotional control [3]. Tailor employs a single pretrained seq2seq model for various perturbations through structured control codes, demonstrating LLMs' adaptability to user-defined attributes [2].

Frameworks like the Writing Path enhance content generation control by incorporating explicit outlines to guide high-quality text production [11]. The RSA-Control method uses mutual reasoning between speaker and listener to enhance attribute control, showcasing the model's pragmatic language management capabilities [32]. LLMs' architecture is enriched by integrating external information sources, such as knowledge graphs (KGs) and knowledge bases (KBs), to provide additional context and factual accuracy [30].

Advanced methodologies like Plan-to-Text Generation (P2T) contribute to reliable outputs by separating text planning from realization, allowing a higher-level narrative structure understanding [11]. The Conditional Variational Auto-Encoder (CVAE) exemplifies the architecture's ability to balance accuracy, diversity, and novelty in phrase generation, highlighting adaptability to various stylistic and semantic constraints [3].

LLMs' architecture and capabilities are marked by their integration of diverse methodologies, such as knowledge access and dynamic prompt adaptation, to enhance text generation processes. As these models evolve, their architectural frameworks are expected to diversify, leading to more advanced solutions for controlled text generation. This evolution will encompass various modulation strategies for key components, enhancing accuracy, coherence, and topicality across applications like scientific literature and structured document creation [9, 4, 5].

3.2 Limitations of Current LLMs

LLMs face several limitations in controlled text generation, primarily due to their reliance on extensive training data, which is scarce for less-resourced languages, limiting multilingual capabilities [32]. This reliance can lead to overfitting when fine-tuned on limited datasets, resulting in hallucinated outputs lacking factual accuracy [26]. Moreover, existing benchmarks often fail to account for uncertainty across different prompts, leading to potential output miscalibration [34].

The black-box nature of LLMs poses challenges in ensuring that generated texts meet specific control attributes, often requiring significant computational resources for fine-tuning, which can produce unexpected outputs [32]. Current methods struggle with preserving original content, particularly when using black-box models, leading to a trade-off between emotional expressiveness and grammatical correctness.

In terms of efficiency, LLMs are hampered by low inference efficiency and noisy results due to heuristic scoring functions in search-based techniques [22]. Preprocessing steps like binarizing dependency trees can reduce parallelism, impacting performance on complex constructions [35]. The trade-off between emotional expressiveness and grammatical correctness remains significant, as models often compromise one for the other [3].

Architectural constraints in maintaining coherence over long dependencies exacerbate these issues, leading to incoherent sentence generation [36]. The lack of explicit content order modeling in neural network-based approaches limits the fluency and coherence of generated text compared to human writing [17].

Figure 3 illustrates the primary limitations of current large language models (LLMs) in controlled text generation, categorized into challenges related to training data, efficiency and coherence, and architectural constraints. It highlights issues such as multilingual limitations, inference efficiency, and dependency modeling. These challenges underscore the need for advancements in model architecture, data efficiency, and semantic understanding to improve LLMs' ability to generate reliable, coherent, and contextually relevant text across diverse applications.

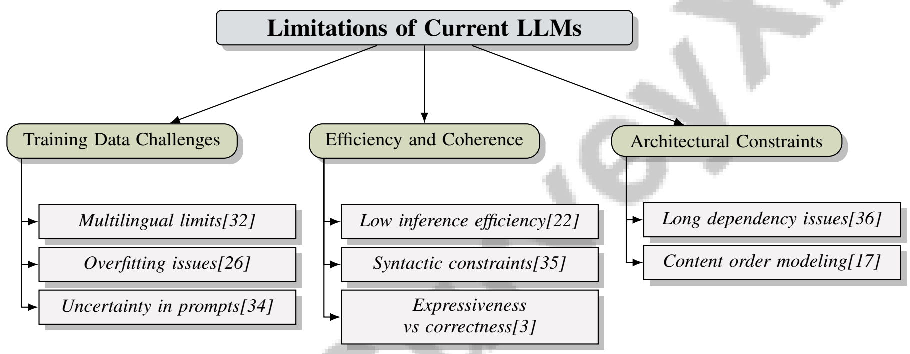

Figure 3: This figure illustrates the primary limitations of current large language models (LLMs) in controlled text generation, categorized into challenges related to training data, efficiency and coherence, and architectural constraints. It highlights issues such as multilingual limitations, inference efficiency, and dependency modeling.

3.3 Advancements and Breakthroughs

Recent advancements in LLMs have significantly impacted text generation, allowing for more sophisticated and precise control over generated content. TextBox 2.0 exemplifies this progress by surpassing original implementations across various metrics, highlighting continuous improvements in model architectures and capabilities [37].

Model arithmetic represents a pivotal advancement, enabling precise control over generated text by blending multiple models and attributes to create outputs aligned with user-defined specifications [38]. This innovation underscores the potential of arithmetic operations in enhancing LLM adaptability and precision, facilitating content generation that meets specific constraints or stylistic requirements.

Transformers, the foundational architecture behind many LLMs, have reshaped NLG standards and enabled sophisticated applications across domains [39]. Their ability to capture complex text dependencies has advanced narrative fluency and coherence, expanding LLM applicability in diverse settings.

Recent advancements in LLMs highlight the field's dynamic evolution, characterized by innovative frameworks and methodologies that enhance text generation capabilities. Systematic task exploration frameworks allow nuanced manipulation of task inputs and outputs, particularly in complex areas like citation text generation. Outline-guided text generation techniques significantly improve the quality and user alignment of generated content. Additionally, literature reviews identify persistent challenges such as bias and hallucinations, while new detection frameworks like CUDRT address complexities in distinguishing between human and LLM-generated texts across languages. These innovations push text generation boundaries and establish a foundation for future NLP research and applications [40, 6, 41, 7, 4]. As models become more adept at managing control attributes and generating contextually relevant text, LLM applications in controlled text generation are poised to grow, offering new opportunities for tailored communication across domains.

4 Controlled Text Generation Techniques

Category	Feature	Method
Prompt Engineering	Token and Embedding Modifications	C-NLG[33]
	Guided Output Techniques	N/A[2]
	Structured and Hierarchical Strategies	CTG[11]
	Evaluation and Constraint Satisfaction	PCAM[10]
	Optimization Strategies	SLUTG[21]
Language Model Fine-Tuning	Control and Constraints	LiFi[1], F-LLM[42], ATGM[3]
	Syntactic Structure Guidance	ITEXP[35]
	Task and Instruction Integration	GENPET[13]
	Iterative Refinement	TGLS[22]
Reinforcement Learning Approaches	Adaptive Control Strategies	RSA[32], ENLG[43]
	Feedback-Driven Optimization	PH[44], RLGF[45]
	Granular Feedback Mechanisms	PARGS[46], PMCTG[20], FPT[47], PDRCM[48], ESPT-T5[49]
	Feedback-Oriented Strategies	FAST[50]
	Divergence Minimization	GDC[51]
	Model Combination Techniques	MA[38]
Constraint-Based Methods	Optimization and Transformation	CFF[52]
	Planning and Control	GGP[53]
	Template and Constraint Techniques	TSMH[54]
	Probability Distribution	Entmax[55]
	Dynamic Monitoring	NRETM[12]
Hybrid and Novel Techniques	Factual and Precision Control	SDS[56], TBS[57]
	Context Adaptation Strategies	TL[58]
	Control Theory Applications	LiSeCo[59], GT-CTG[60]
	Narrative Coherence Enhancement	PLANET[61]

Table 1: This table presents a comprehensive summary of various controlled text generation techniques categorized into five main areas: Prompt Engineering, Language Model Fine-Tuning, Reinforcement Learning Approaches, Constraint-Based Methods, and Hybrid and Novel Techniques. Each category is further detailed with specific features and methods, highlighting the diverse strategies employed to enhance the precision and adaptability of large language models (LLMs) in producing text that adheres to user-defined constraints.

The exploration of controlled text generation has gained momentum, driven by the need for language models to produce outputs that adhere to specific user-defined constraints. Table 5 provides a detailed overview of controlled text generation techniques, illustrating the diverse methodologies and innovations that facilitate the production of text aligned with specific user-defined criteria. This section examines various techniques facilitating controlled text generation, emphasizing innovative methodologies that enhance the precision and adaptability of large language models (LLMs). The following subsection will focus on prompt engineering, a critical technique guiding LLMs in generating outputs aligned with predetermined criteria, setting the stage for deeper insights into its implications and applications.

4.1 Prompt Engineering

Method Name	Control Techniques	Optimization Methods	Application Scenarios
N/A[2]	Semantic Role Codes	Unlikelihood Training	Contrast Sets
TGLS[22]	Simulated Annealing	Heuristic Scoring Functions	Low-resource Language
SLUTG[21]	Heuristic Scoring Function	Discrete Local Search	Grammatical Error Correction

Table 2: Overview of various methods for controlled text generation, highlighting their respective control techniques, optimization methods, and application scenarios. The table includes methods such as N/A, TGLS, and SLUTG, each utilizing different strategies to enhance prompt engineering for large language models.

Prompt engineering is crucial in guiding large language models (LLMs) for controlled text generation, enabling outputs that meet specific user-defined criteria. This technique involves crafting input prompts to direct the model's output, ensuring adherence to desired attributes. The method by [2] highlights the effectiveness of generating text conditioned on structured control codes, showcasing prompt engineering's potential in refining LLM outputs.

In unsupervised text generation, [22] introduces TGLS, using simulated annealing and a conditional generative model, emphasizing prompt engineering's role in framing text generation as a search problem. Similarly, [21] presents SLUTG, employing heuristic scoring to iteratively refine candidate sentences, illustrating prompt engineering's impact on text quality. Table 2 provides a comprehensive comparison of different methods employed in prompt engineering for controlled text generation, detailing their control techniques, optimization methods, and application scenarios.

Prompt engineering extends to preprocessing inputs with desired conditions, modifying token embeddings, and adjusting self-attention mechanisms. The hierarchical model by [36] underscores structured plan extraction's significance, highlighting planning's role in controlled text generation.

Overall, prompt engineering is vital for advancing controlled text generation, offering solutions for guiding LLMs to produce high-quality, user-aligned text. As natural language processing (NLP) advances, integrating structured control codes, heuristic scoring, and iterative search methods will enhance prompt engineering's precision and efficacy. This evolution is significant given the shift towards holistic, end-to-end multi-task learning paradigms facilitated by LLMs like GPT-3 and GPT-4. These sophisticated techniques optimize text generation in applications like conversational agents and grammatical error correction, addressing challenges in low-resource languages and minimizing extensive human annotation [62, 21].

4.2 Language Model Fine-Tuning

Fine-tuning is pivotal in adapting large language models (LLMs) for controlled text generation, enabling them to meet specific constraints. This involves refining pretrained models on additional datasets, enhancing their ability to generate text aligned with control parameters. The TGLS method exemplifies this by alternating between search and learning phases, coupling these processes to improve text quality [22].

Fine-tuning integrates auxiliary tasks, enhancing content and attribute control by incorporating content inputs, allowing for precise alignment with user specifications. Feedback-aware self-training generates counterfactual examples and filters noisy data, addressing spurious correlations that mislead models, ultimately improving text quality [50, 63, 64, 65, 66].

Fine-tuning enhances LLM performance by incorporating instructions and labeled examples, improving data efficiency in controlled text generation. It allows LLMs to generalize across tasks with limited labeled data and leverages synthetic data generation for smaller models, reducing computational resources. Reinforcement learning techniques refine output quality, enabling smooth control over text attributes, leading to superior performance in diverse tasks [28, 67, 45]. Training attribute classifiers on labeled data achieves precise control over generated outputs.

Fine-tuning is crucial for adapting LLMs to generate controlled text, enhancing their ability to meet constraints across applications. Techniques like synthetic data generation and targeted attribute control improve smaller models' performance and allow nuanced text generation adjustments, including conciseness and emotional tone. This adaptability ensures generated content aligns with desired context and user expectations, facilitating effective communication in various scenarios [28, 67]. As the field progresses, efficient fine-tuning techniques will continue to enhance LLMs' capabilities in generating high-quality, controlled text.

4.3 Reinforcement Learning Approaches

Reinforcement learning (RL) is pivotal for enhancing controlled text generation, providing a framework for models to learn optimal strategies through iterative feedback. RL in text generation is exemplified by using web crawling and RL for engaging summaries, showcasing RL's potential in synthesizing coherent content [43]. This method leverages RL's dynamic nature to refine outputs, ensuring adherence to user-defined goals.

The RLGF method surpasses traditional RL techniques like Proximal Policy Optimization (PPO), demonstrating guided feedback's effectiveness in fine-tuning LLMs for specialized tasks [45]. This advancement underscores RL's capacity to enhance model adaptability and precision, aligning text with desired attributes.

The RSA-Control method introduces a self-adjustable rationality parameter, enabling dynamic control strength modulation based on context [32]. This flexibility allows nuanced control over text generation, adapting to varying user-defined constraints and enhancing content quality.

The Prompt Highlighter approach illustrates RL's role in controlled text generation by guiding autoregressive generation through adjusted attention scores [44]. This technique produces outputs closely aligned with user needs, highlighting RL's adaptability in managing prompt-based interventions.

Reinforcement learning approaches hold promise for enhancing controlled text generation by aligning model outputs with user-defined constraints, evidenced by advancements incorporating token-level feedback and dense reward mechanisms. These innovations improve training efficiency—making it 2.5 times more sample-efficient and 7 times faster—and significantly boost text quality, achieving over 21

4.4 Constraint-Based Methods

Method Name	Constraint Integration	Optimization Techniques	Control Mechanisms
GGP[53]	Explicit Control Text	Combinatorial Optimization Techniques	Structured Planning Process
CFF[52]	Constraint Programming Integration	Combinatorial Optimization Problem	Constraint Programming Framework
NRETM[12]	Logical Constraints	-	Dynamic Tracking
Entmax[55]	Entmax Transformation	Entmax Sampling	Sparse Probability Distribution

Table 3: This table provides a comprehensive comparison of various constraint-based methods employed in controlled text generation. It details the integration of constraints, optimization techniques, and control mechanisms used by each method, highlighting their unique approaches to enhancing text generation flexibility and control.

Constraint-based methods in controlled text generation involve implementing specific rules and conditions that guide language models' output, ensuring alignment with predefined attributes. These methods leverage a modular framework incorporating multiple differentiable constraints during decoding, transforming it into a continuous optimization problem. This enhances text generation flexibility and reduces computational costs, facilitating efficient control over textual attributes in applications like scientific literature generation and style transfer [68, 4]. These methods maintain content quality and relevance, especially in complex applications requiring precise control. Table 3 presents a detailed comparison of constraint-based methods in controlled text generation, showcasing their distinct approaches to integrating constraints, optimization, and control mechanisms.

The GGP (Graph-based Grouping Planner) method exemplifies explicit control in text generation by creating a detailed plan from key phrases before generating text [53]. This ensures generated content aligns with intended structure and thematic elements, offering high output control.

Transforming constrained text generation into a combinatorial optimization problem, as demonstrated by [52], employs constraint programming to solve optimization, generating text adhering to multiple constraints. This is effective where traditional methods struggle with complex constraint interactions.

COLLIE introduces a grammar-based framework for specifying rich, compositional constraints across text generation levels [31]. This integrates complex grammatical rules, enhancing model adaptability and precision in producing text meeting specific constraints.

The Neural Rule-Execution Tracking Machine (NRETM) uses a dynamic tracking mechanism managing multiple logical constraints, crucial for generating text with intricate dependencies [12]. This ensures output coherence and contextual relevance.

Entmax sampling by [55] introduces a natively sparse probability distribution, enhancing text generation control by allowing nuanced probability distribution adjustments, ensuring alignment with constraints.

Constraint-based methods systematically integrate rules and conditions—such as structural and thematic constraints—directing language models' outputs. These methods enhance models' ability to conform to user-defined requirements, addressing challenges in generating high-quality text across applications. Techniques like prompt engineering, optimization algorithms, and internal knowledge leveraging refine LLMs' generative capabilities, ensuring outputs meet qualitative standards and user needs [10, 23, 68, 4, 69]. These techniques contribute to advancing controlled text generation, aligning model outputs with user-defined constraints.

4.5 Hybrid and Novel Techniques

Method Name	Methodological Integration	Control Mechanisms	Application Scenarios
SDS[56]	Early Stopping	Semantic Drift Score	Wikipedia-style Biographies
TBS[57]	Search Trees	Confidence-based Sampling	Creative Text Generation
LiSeCo[59]	Control Theory Integration	Control-theoretic Intervention	Toxicity Avoidance Tasks
GT-CTG[60]	Game-theoretic Framework	Strategic Prompt Interventions	Controlled Text Generation
PLANET[61]	Dynamic Content Planning	Semantic Planning Representations	Coherent Long-form Text

Table 4: Comparison of hybrid and novel techniques for controlled text generation, detailing methodological integration, control mechanisms, and application scenarios. The table highlights the diverse approaches and frameworks, such as semantic drift scores, search trees, and game-theoretic frameworks, which enhance the precision and flexibility of language models in various contexts.

Hybrid and novel techniques in controlled text generation advance the field by combining methodologies to enhance language models' precision and flexibility. The introduction of a semantic drift score quantifies correct and incorrect fact separation, enabling effective generation process control [56]. This maintains factual integrity in applications where accuracy is crucial.

Combining search trees with confidence-based sampling represents a hybrid technique for controlled text generation [57]. This method leverages search-based and probabilistic approaches, allowing nuanced generation process control, ensuring outputs align with constraints.

LiSeCo introduces a control-theoretic intervention guaranteeing output steering into allowed regions with minimal computational overhead [59]. This integrates control theory into text generation, offering systematic output management.

Systematic and principled mixing of representation levels, highlighted by [70], provides flexible and efficient text generation. This integrates various representational forms, enhancing adaptability to diverse inputs and constraints.

Nash equilibrium in controlled text generation optimizes directive and narrative prompts balance, achieving high-quality content through stable strategy profiles [60]. This game-theoretic approach refines language models' control mechanisms.

PLANET, a novel framework dynamically integrating content planning and surface realization in autoregressive Transformers, advances hybrid techniques [61]. This enhances narrative coherence and relevance, offering comprehensive controlled text generation solutions.

Table 4 provides a comprehensive comparison of hybrid and novel methodologies in controlled text generation, illustrating the integration of diverse techniques and their respective applications. Hybrid and novel techniques in controlled text generation reflect field evolution, evidenced by scientific literature modulation strategies and sequentially controlled text generation methods. These approaches enhance language models' precision, flexibility, and efficiency, introducing new architectures leveraging a comprehensive schema of crucial components. Increasing structural awareness in text generation improves control accuracy, grammaticality, coherence, and topicality, achieving writing performance resembling human standards [4, 5]. These techniques will advance the field, offering tailored communication opportunities across applications.

Feature	Prompt Engineering	Language Model Fine-Tuning	Reinforcement Learning Approaches
Control Technique	Structured Control Codes	Auxiliary Tasks	Token-level Feedback
Optimization Method	Iterative Search Methods	Reinforcement Learning	Dense Reward Mechanisms
Application Scenario	Conversational Agents	Low-resource Languages	Text Style Transfer

Table 5: The table provides a comparative analysis of various controlled text generation techniques, highlighting their control techniques, optimization methods, and application scenarios. It underscores the distinct methodologies employed in prompt engineering, language model fine-tuning, and reinforcement learning approaches, elucidating their roles in enhancing the precision and adaptability of large language models.

5 Applications of Controlled Text Generation

Controlled text generation finds applications across various domains, addressing specific challenges and enhancing processes. In education, it significantly impacts learning outcomes and resource accessibility by creating tailored educational materials that support pedagogical goals and cater to diverse learner needs. The following subsection explores its applications in the educational sector, highlighting its transformative potential in shaping modern educational practices.

5.1 Education

Controlled text generation transforms education by creating customized educational content that aligns with pedagogical goals and learning standards. Models like GeneUS automate user story creation in software engineering, streamlining content creation processes in educational settings [71]. The ability to control text attributes such as sentiment, formality, and toxicity is crucial for producing pedagogically effective content. The Locate and Edit (LE) framework effectively manages sentiment control and formality transfer, ensuring content appropriateness across educational contexts [72].

The Affective Text Generation Model (ATGM) exemplifies adaptability in dialogue systems and therapeutic chatbots, offering personalized learning experiences and support in educational and mental health contexts [3]. Datasets like COLLIE-v1, constructed from real-world data, provide a foundation for developing educational content adhering to specific constraints, ensuring accuracy and relevance [31].

Integrating controlled text generation (CTG) in education enhances content quality, relevance, and accessibility while reducing teacher workloads by generating high-quality, diverse educational questions. Recent advancements in CTG methods improve classroom interactions and learning outcomes, with evaluations showing teachers find the generated questions useful and pedagogically sound. This approach paves the way for new architectures that refine educational content tailored to diverse learning needs [4, 18]. As these techniques evolve, they are poised to advance educational methodologies and improve learning outcomes, making education more personalized and effective worldwide.

5.2 Healthcare

In healthcare, controlled text generation promises to enhance patient communication, medical documentation, and decision support systems. Advanced techniques improve clinical documentation quality and efficiency by ensuring generated text adheres to medical guidelines and standards, enhancing coherence, grammatical accuracy, and topical relevance [5, 6, 9, 4, 73]. Automating medical report generation involves leveraging advanced techniques to produce comprehensive, accurate, and verifiable reports, enhancing clinical documentation practices [6, 4, 74, 5].

Controlled text generation develops patient education materials tailored to individual needs and health literacy levels. Precise control over readability, tone, and sentiment enhances patient engagement and adherence to treatment plans. Advanced techniques ensure content aligns with desired stylistic and semantic characteristics, addressing distribution shifts in user prompts [64, 28].

In mental health, controlled text generation facilitates therapeutic chatbots and virtual assistants, offering personalized support and guidance. Emotion-conditioned text generation meticulously controls emotional tone and content, enhancing therapeutic experiences [3, 4, 75]. Clinical decision support systems benefit from generating evidence-based recommendations and alerts, aiding clinicians in informed decision-making. Integrating structured and unstructured data sources delivers insights enhancing clinical workflows and patient outcomes [76, 5, 6, 9, 4].

Overall, controlled text generation offers transformative potential in healthcare, enhancing communication, documentation, and decision-making processes. As technologies like large language models and controllable text generation advance, they are expected to significantly enhance healthcare delivery and patient care by generating accurate, verifiable, and contextually relevant reports tailored to individual patient needs [6, 4, 74].

5.3 Content Creation and Storytelling

Controlled text generation is pivotal in content creation and storytelling, enabling narratives that adhere to specific constraints while maintaining coherence and engagement. The GGP method demonstrates superior performance in generating coherent long texts through structured planning [53]. The PHVM framework showcases practical applications in advertising text and recipe generation [77]. The LiFi framework exemplifies potential in crafting narratives aligning with specific stylistic requirements [1].

The TGLS framework's potential in paraphrasing and formalizing text is crucial for adapting content to different contexts and audiences [22]. The search and learning approach for unsupervised text generation provides innovative solutions for high-quality text generation without extensive labeled datasets [21]. ITEXP enhances control over syntax and generation efficiency, ensuring high syntactic quality in narratives [35].

Experiments in generating news headlines, meta reviews, and search ads demonstrate real-world applications of controlled text generation [50]. Controlled text generation advances content creation and storytelling, crafting narratives aligned with specific user-defined constraints. As techniques evolve, particularly through large language models (LLMs) and structured writing frameworks, they enhance storytelling methodologies, improving content quality and coherence while opening innovative avenues for creative expression [6, 7, 4].

5.4 Business Process Management

Controlled text generation significantly impacts Business Process Management (BPM) by enhancing information extraction efficiency and accuracy from unstructured textual documents. Large Language Models (LLMs) perform complex BPM tasks, processing and generating text with high contextual relevance and coherence [78]. LLMs mine imperative and declarative process models, essential for understanding and optimizing business workflows, facilitating the creation of process models reflecting underlying business operations.

LLMs assess task suitability for robotic process automation (RPA), streamlining RPA integration and enhancing overall process efficiency [78]. Controlled text generation develops intelligent systems supporting decision-making processes by analyzing extensive volumes of unstructured textual data, improving operational efficiency and fostering responsive organizational strategies [19, 41, 78, 40]. As technologies evolve, they transform BPM practices, offering innovative solutions for optimizing business processes and enhancing organizational performance.

5.5 Media and Entertainment

Controlled text generation transforms media and entertainment by enabling innovative content creation, curation, and personalization solutions. Advanced methodologies, such as sequentially controlled text generation, enhance longer text coherence and structure, improving generated content quality. Large pre-trained language models boost performance in natural language generation tasks, including machine translation and text summarization, facilitating tailored content production [20, 5, 6, 11, 4].

In media, controlled text generation automates news article generation, producing content adhering to editorial guidelines and styles. This capability is valuable for timely reporting, such as breaking news, generating coherent, accurate articles maintaining the publication's voice and tone. Controlled text generation personalizes media content by dynamically tailoring articles and recommendations based on user preferences, enhancing reader engagement and satisfaction [4, 5].

In entertainment, controlled text generation creates interactive storytelling experiences, allowing dynamic narratives responding to user inputs. Techniques like controlled cue generation and game-theoretic frameworks ensure narratives are relevant, coherent, and emotionally resonant [60, 79]. Controlled text generation creates virtual characters and chatbots, engaging users in natural, context-aware conversations, enhancing user experience [25, 5].

Integrating controlled text generation in media and entertainment streamlines content production and opens new avenues for creative expression and audience interaction. As technologies advance, they transform media and entertainment landscapes, enhancing content quality and allowing greater personalization across platforms. This evolution, driven by large language models (LLMs) and structured writing techniques, facilitates collaborative content creation, improves alignment with user intentions, and ensures content adheres to expert-defined standards, boosting accuracy and user satisfaction [6, 7, 4, 80].

6 Challenges and Limitations

Exploring the challenges and limitations of controlled text generation (CTG) involves addressing ethical, computational, and resource-related issues. Ethical concerns, particularly biases and misuse potential, require careful consideration of the responsibilities tied to deploying these technologies. Additionally, the computational demands of fine-tuning large language models (LLMs) and resource constraints pose significant barriers to scalability and effectiveness. The following subsections delve into these complexities, beginning with the ethical concerns surrounding bias, misuse potential, and responsible technology use.

6.1 Bias, Ethical Concerns, and Misuse Potential

CTG faces ethical challenges primarily due to biases in LLMs and misuse potential. These models often perpetuate biases from training data, raising concerns about reinforcing stereotypes and producing biased content [13]. The limited interpretability of deep neural networks exacerbates these issues, complicating efforts to ensure quality and constraint adherence in generated text [3]. Misuse of CTG methods for harmful content is a significant concern, with model arithmetic posing risks for deceptive outputs. Writing non-diegetic prompts can disrupt flow, raising ethical concerns about user experience and accessibility [36]. Ensuring reliability and trustworthiness in CTG systems is crucial, particularly to prevent misinformation and deceptive content, necessitating robust evaluation frameworks [30, 74]. The black-box nature of models complicates adherence to constraints, especially with complex logical conditions. Addressing misuse potential requires robust detection systems and ethical guidelines. Automated extraction and filtering processes in CTG can lead to quality issues, compromising reliability and benchmarks. Large-scale pre-trained language models (PLMs), despite producing diverse and fluent text, lack interpretability and controllability, potentially leading to errors or unhelpful content [74, 17, 20, 18]. Addressing ethical concerns and misuse potential is vital for responsible CTG deployment, given NLG's capabilities to produce human-like text, which risks misinformation, fake reviews, and privacy violations. Literature reviews highlight nine challenges, including bias and interpretability, emphasizing the need for robust mitigation strategies and ethical frameworks [6, 30, 4]. Implementing safeguards and fostering awareness can harness CTG's benefits while mitigating risks, ensuring positive societal contributions.

6.2 Computational and Resource Limitations

CTG is significantly impacted by computational and resource limitations, challenging scalability and effectiveness. Fine-tuning LLMs requires substantial computational resources, often prohibitive in resource-constrained environments [71]. The complexity of selecting and optimizing transformation networks complicates maintaining representation integrity [35]. Non-deterministic LLM outputs require translation into formalized languages, adding computational burden [10]. Current methods struggle with controlling multiple subjects without retraining, highlighting inefficiencies [1]. Focused prefix tuning (FPT) methods, while improving control, incur higher time costs, underscoring computational constraints [1]. Structured training data reliance poses challenges, as methods depend on data availability, limiting scalability [22]. Token limits in text encoding challenge diffusion models, affecting output quality [2]. Natural Language Inference (NLI) strategies' inefficiency can slow generation, especially with multiple iterations required [33]. Enhancing CTG requires addressing these limitations through efficient models and methodologies, crucial for meeting demands for high-quality, contextually relevant text. Modulation strategies and control techniques, including model retraining, fine-tuning, and prompt engineering, can improve generation. Integrating external knowledge into models enhances performance in real-world applications. Systematically addressing these challenges can expand CTG applicability and effectiveness [23, 4, 17, 9].

6.3 Control Mechanisms and Attribute Management

Implementing control mechanisms and effective attribute management in CTG presents challenges, given the technology's sophistication and accessibility. Generating contextually appropriate cues without extensive manual intervention is difficult, as existing methods often fail to achieve this [14]. Controlling explanation generation in specified formats is another obstacle, leading to omissions and ambiguities [81]. Lack of fine-grained sentence-level planning can cause coherence errors, especially in complex narratives. Hierarchical structures and planning mechanisms, like those in the PHVM framework, show potential for managing attributes and maintaining coherence [77]. However, even advanced planning mechanisms may struggle with complex narratives, indicating a need for further advancements in control mechanisms and attribute management [53]. Addressing these challenges requires ongoing research to enhance language model precision and reliability. By tackling challenges like bias, reasoning, and hallucinations, researchers can improve text quality and coherence, ensuring outputs meet user-defined constraints and adapt to various applications. Knowledge-enhanced text generation techniques facilitate external knowledge incorporation, leading to more accurate and contextually relevant results [6, 9].

6.4 Long Text Generation and Coherence

Generating coherent long texts with controlled attributes poses challenges, particularly in maintaining narrative coherence and logical progression. Current models struggle with content selection and ordering, crucial for coherent long-form narratives [61]. Lack of explicit mechanisms for event transitions and thematic consistency can lead to disjointed outputs. Effective planning of event transitions ensures logical narrative flow, requiring innovative approaches [82]. Managing multiple attributes, such as style, tone, and factual consistency, adds complexity. Models must generate contextually relevant, logically ordered content while adhering to constraints. Achieving narrative coherence with attribute requirements necessitates nuanced approaches, as contemporary models struggle with bias, reasoning difficulties, and interpretability [6, 7]. Advancements in content planning and event transition management, through structured approaches and auxiliary tasks, are needed to enhance text reasoning and organization [6, 5, 83]. Developing sophisticated models to organize and integrate narrative elements can improve long-form text quality and coherence, ensuring outputs meet user expectations and maintain thematic integrity across applications.

7 Future Directions

Exploring future directions in controlled text generation (CTG) involves advancing model architecture and training methodologies to overcome current limitations. These advancements are crucial for enhancing model capabilities and addressing inherent challenges. This section focuses on specific enhancements in model architecture and training, highlighting innovative approaches that could significantly improve CTG systems' efficacy and adaptability.

7.1 Enhancements in Model Architecture and Training

Advancements in model architecture and training methodologies are vital for progressing CTG. Future research should automate the generation of effective task descriptions for natural language generation (NLG) systems to improve models' contextual comprehension and emotional dynamics navigation. This is pertinent given challenges like bias, reasoning, and interpretability in text generation [6, 84, 40]. Systematic input manipulation and evaluation metrics, as applied in citation and personalized text generation studies, could enhance models' adaptability to diverse contexts and tasks.

Improving models like LiFi across tasks suggests potential architectural and training enhancements [1]. Refining control code design and integrating additional semantic representations could enhance models like Tailor, providing precise control over generated text [2]. Advancements in search algorithms and noise robustness are critical, necessitating efficient search techniques and better scoring functions. Expanding benchmarks with more datasets and metrics could enhance model applicability across language generation tasks [36].

Focusing on knowledge integration, evaluation methodologies, and semantic validity enhancement can significantly advance language technologies. This will lead to more sophisticated, reliable, and adaptable solutions addressing coherence, reasoning, and grammatical accuracy challenges, improving applications in automated content generation, customer service, and educational technology [6, 9, 4, 8].

7.2 Advanced Control Mechanisms

Developing advanced control mechanisms is crucial for enhancing language models' precision and adaptability. These mechanisms enable models to generate text that aligns with specific constraints, improving output quality and relevance. Reinforcement learning offers an innovative approach, allowing models to refine outputs iteratively based on feedback, ensuring adherence to desired attributes [43].

Control-theoretic interventions, like those in LiSeCo, demonstrate the potential of advanced control mechanisms to guide outputs with minimal computational overhead [59]. Nash equilibrium strategies provide a novel framework for optimizing content quality through stable strategy profiles [60]. Dynamic prompt adaptation, as shown by RSA-Control, illustrates advanced mechanisms' potential to adjust control strength contextually, enhancing adaptability [32].

These developments represent a transformative leap in CTG, offering strategies to align outputs with user-defined constraints and attributes. Techniques such as sequentially controlled text generation and methods for model retraining, fine-tuning, and prompt engineering are explored to improve content coherence and quality. This progress addresses large language models' limitations and opens avenues for future research to refine these methods, aiming for human-level writing performance across applications [23, 4, 17, 5].

7.3 Applications and Domain-Specific Adaptations

Future CTG research will explore diverse applications and domain-specific adaptations, enhancing language models' versatility across fields. In education, integrating generated questions into classrooms and extending frameworks like STANDARDIZE to other languages could refine pedagogical approaches [85]. Multilingual generation leveraging universal POS tags offers opportunities for real-world data-to-text applications, addressing language disparities in educational and professional settings [6, 86].

In societal impact, frameworks like NADO could address biases in generated text, promoting equitable content generation. Enhancing referring expression generation and methodologies for managing unseen entities can elevate text generation systems' quality and efficiency, crucial in complex domains [6, 9]. In business process management, applying LLMs to BPM tasks and improving prompt designs could enhance output quality [78].

Expanding text generation libraries and enhancing training efficiency are critical for broadening language models' applicability. Integrating structured frameworks in cross-lingual contexts and enhancing citation intents' informativeness can propel academic writing and research advancements, improving scholarly communications' quality and relevance [40, 6, 8, 7, 4]. Addressing these directions will develop sophisticated, reliable, and adaptable solutions for scientific literature generation, structured long-form writing, and knowledge-enhanced text creation [17, 5, 6, 9, 4].

7.4 Ethical and Societal Implications

CTG advancements present significant ethical and societal implications requiring careful consideration and proactive measures. A primary concern is CTG models' potential to perpetuate biases, generating harmful content. Robust model development and bias detection mechanisms are necessary to mitigate these risks and ensure ethical alignment [19].

Privacy-preserving practices are crucial, given the sensitive data models may process. Ensuring compliance with regulatory standards protects user privacy and maintains trust. Developing parameter-efficient models can reduce computational footprints and sensitive information exposure [19].

CTG's societal implications extend to potential misuse, such as generating misleading content, highlighting the need for regulatory frameworks ensuring ethical use. Incorporating ethical guidelines and transparency in LLM development addresses concerns like data bias and academic integrity, promoting responsible technology use [19, 7, 74, 87].

Addressing CTG's ethical and societal challenges, such as bias and misinformation, requires sustained engagement from researchers, developers, and policymakers. Prioritizing ethical considerations and implementing safeguards can harness CTG's benefits while minimizing harms, ensuring these technologies serve the greater good [6, 30, 9, 4].

8 Conclusion

The survey underscores the pivotal role of controlled text generation (CTG) in advancing natural language processing (NLP), highlighting how transformer-based pre-trained language models (PLMs) have significantly enhanced text generation capabilities. Despite these strides, challenges persist in achieving precise control and maintaining text quality. Innovative methodologies, such as the SCTG method, demonstrate promising improvements in structural coherence and text quality, approaching human-level performance. This highlights the potential of ongoing research to refine CTG techniques further.

The superior performance of CriticControl across various tasks emphasizes the importance of continuous exploration in refining CTG methods to produce coherent and controlled outputs. The architecture of PLMs remains crucial in optimizing text generation results, necessitating further investigation to enhance their applicability and effectiveness. Current evaluations indicate that while large language models (LLMs) are adept at generating rationales and adhering to broad control signals, they struggle with implementing precise constraints.

There is a clear need for robust evaluation frameworks that combine human judgment with automated metrics to improve the accuracy and reliability of CTG assessments. As the field evolves, developing more sophisticated models and evaluation methods will be essential to overcome existing limitations and expand CTG's capabilities. This ongoing research and development are critical for ensuring that CTG continues to evolve and make positive contributions to the broader NLP landscape.

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