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 is a pivotal advancement in natural language processing (NLP) that enables the production of text conforming to specific constraints or user-defined attributes. This capability is essential for applications demanding tailored communication, significantly enhancing user experience and satisfaction. The increasing demand for precise control mechanisms in text generation highlights its critical role in addressing the inefficiencies of existing autoregressive models, which often yield suboptimal syntactic structures and diminished diversity [1, 2].

The importance of controlled text generation lies in its ability to maintain fluency and coherence while adhering to specified constraints, ensuring that generated text is relevant and aligns with user intentions. This is particularly crucial in scenarios requiring the customization of attributes such as sentiment and readability [3]. Furthermore, it facilitates the generation of emotionally nuanced text without sacrificing grammatical integrity, thereby enhancing the overall quality and impact of the content.

Controlled text generation is also vital in mitigating the misuse of NLP systems, particularly concerning the generation of deceptive content, such as fake news and misinformation. As advancements in natural language generation (NLG) technologies enable the production of text that closely resembles human writing, the risk of exploitation by malicious actors increases. This encompasses not only misleading articles but also fraudulent online reviews and the use of chatbots to extract sensitive information. Research is focused on developing methods for controlled text generation that ensure

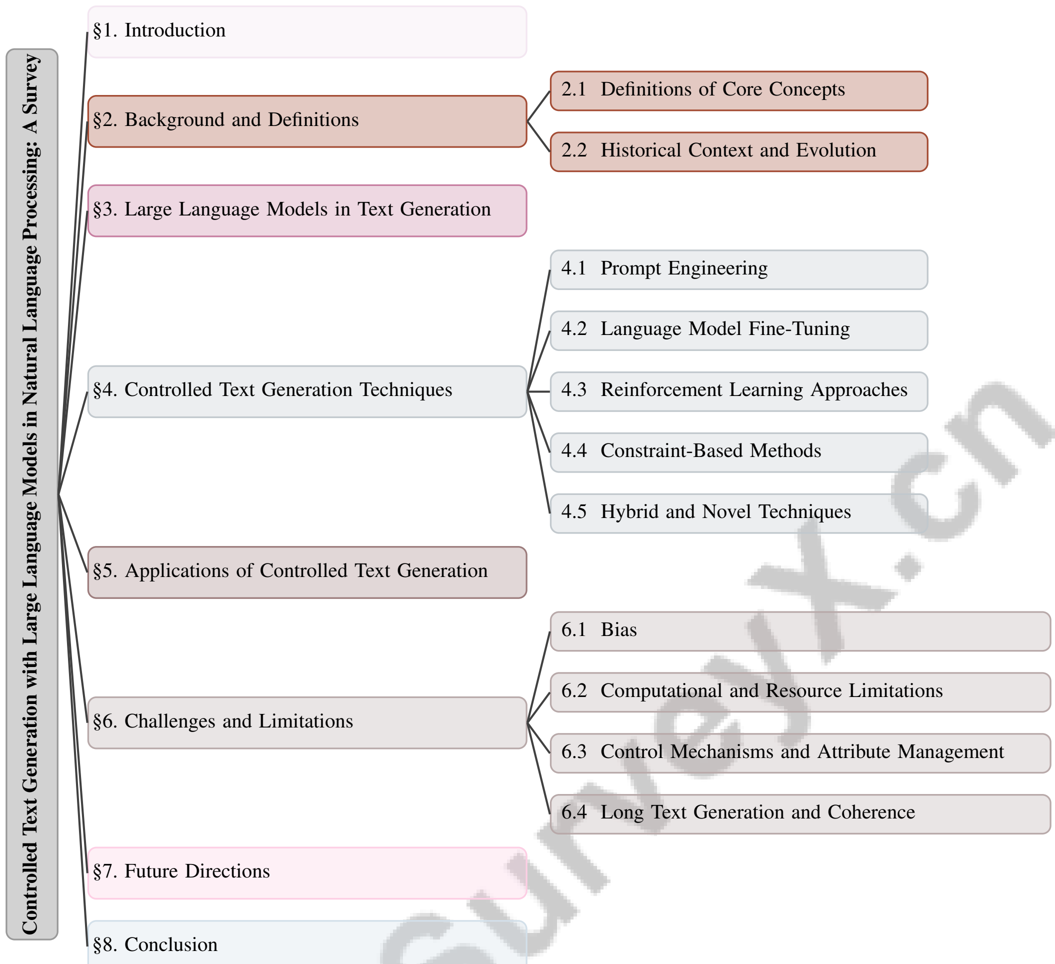

Figure 1: chapter structure

adherence to factual content, thereby enhancing the reliability of NLG systems and addressing challenges related to creativity and fairness in open-domain text generation [4, 5].

As the demand for personalized and context-aware communication grows, particularly in NLG, controlled text generation has emerged as a critical research area. This field encompasses various techniques, including transformer-based pre-trained language models, which improve the diversity and fluency of generated text while addressing interpretability and controllability challenges. Recent advancements, such as sequentially controlled text generation, aim to impose structure and coherence in longer documents, enhancing overall content quality. A systematic literature review underscores the various tasks and challenges in text generation, emphasizing the need for innovative approaches to ensure accuracy, grammaticality, and topical relevance [6, 7, 8, 9]. Thus, controlled text generation is essential for producing high-quality, goal-oriented text that accurately reflects user requirements, solidifying its importance in the evolving landscape of language technologies.

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

Large Language Models (LLMs) are integral to the progress of controlled text generation due to their ability to transform structured inputs into coherent, contextually relevant narratives. Models like GPT-2 and GPT-3 exemplify the potential of LLMs in generating fluent and contextually accurate text [10]. The hierarchical generation framework proposed by [11] illustrates how separating content planning from surface realization can enhance creativity and coherence, showcasing LLMs' capabilities in structured text generation.

AI-generated, for reference only.

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 signifies LLMs' role in providing users with greater control over generated content, a crucial aspect of controlled text generation. Similarly, the GENPET method employs pretrained language models to increase text generation efficiency, further underscoring the importance of LLMs in this domain [13].

In terms of emotional and semantic control, the Affective Text Generation Model (ATGM) modifies the GPT-2 architecture, allowing users to manage both the category and intensity of emotion in generated text [3]. This adaptability 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 LLMs' role in controlled text generation [2].

Despite their robust capabilities, LLMs encounter challenges related to unpredictability and resource-intensive fine-tuning [10]. To mitigate these issues, lightweight frameworks such as LiFi, which employs fine-grained control codes, have been proposed to enhance LLM controllability without extensive computational demands [1]. These advancements highlight the ongoing evolution of LLMs in controlled text generation, emphasizing their significance in generating 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, this survey addresses existing knowledge gaps and offers insights into various text generation tasks and associated challenges [9]. 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].

A 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 broadening 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 the understanding of current approaches, tasks, and evaluation methods in CTG, ultimately contributing to the advancement of the field [8].

1.4 Structure of the Survey

This survey systematically explores 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. It 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 controllable text generation (CTG) are explored across various fields, including education—where it enhances question generation to alleviate teachers' workloads and improve content quality—healthcare, where it assists in patient communication and documentation, content creation that streamlines the writing process, business process management for optimizing workflow documentation, and media and entertainment by generating scripts and interactive content. This underscores the versatility and potential impact of CTG in transforming these domains [6, 17, 18, 19, 9].

The survey also addresses challenges and limitations associated with CTG, including ethical concerns, computational constraints, and the difficulties of maintaining text quality while enforcing constraints. These discussions are essential for identifying and addressing the current challenges and limitations faced in the effective implementation of CTG, particularly in educational contexts where generated questions must meet quality and relevance standards required by teachers [18, 19, 9, 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 an essential component of natural language processing (NLP) that focuses on creating text with specific attributes like sentiment, style, or factual accuracy [1]. Unlike traditional text generation, which often lacks precision, CTG ensures alignment with semantic, syntactic, or stylistic guidelines, enhancing narrative coherence and diversity, especially in applications requiring tailored readability [21, 3]. Large language models (LLMs) such as GPT-3 and BERT are central to CTG, enabling coherent and contextually relevant text generation across tasks like summarization and translation [12]. However, challenges persist when generated text deviates from training data, necessitating integration with structured and unstructured knowledge bases for adaptability to diverse linguistic inputs [2]. Long-term content planning in multi-sentence generation remains a significant challenge [22].

Key CTG concepts include faithfulness, factual consistency, and Natural Language Generation (NLG), crucial for accuracy and reliability [13]. Emotion-conditioned text generation leverages extensive datasets for nuanced emotional control [3]. CTG also involves steering outputs to avoid undesirable content while maintaining quality [10]. Prompt engineering is vital in refining the generation process, particularly in low-resource settings [23]. CTG addresses challenges in producing text that adheres to specific constraints, such as numerical planning, evaluated through specialized benchmarks [21].

Controlled table-to-text generation transforms tabular data into narratives guided by user input, extending to automated speech generation and disinformation, essential for understanding CTG's political implications [2]. CTG's capacity to produce controlled, high-quality text across domains highlights its significance in advancing NLP, ensuring alignment with user-defined constraints [1]. Definitions also cover internal and external knowledge enhancements, such as topics and knowledge graphs, alongside challenges like generating concise text from similar messages without losing clarity [21].

CTG involves creating coherent, diverse long texts from structured data, as in product descriptions and recipes [24]. This entails crafting narratives from key facts while ensuring factual adherence [23]. CTG also refers to generative models' ability to produce text in multiple styles, overcoming limitations of models restricted to fixed styles [24]. The inefficiency and inflexibility of current NLG methods, reliant on complex linguistic components or rigid templates, underscore the need for adaptable CTG approaches [21].

2.2 Historical Context and Evolution

The development of controlled text generation (CTG) and large language models (LLMs) is intertwined with the evolution of natural language processing (NLP) and deep learning, particularly transformer-based models [8]. Early CTG methods relied on rule-based and template-based approaches, which, despite some effectiveness, lacked flexibility for complex linguistic tasks [21]. These methods were constrained by manually crafted logical forms and templates, making them costly and impractical for dynamic applications [25].

The advent of Long Short-Term Memory (LSTM) networks marked a significant improvement in context retention over long sequences. However, the Transformer architecture revolutionized the field by modeling dependencies between words regardless of their positions, foundational in modern

NLP and enabling powerful LLMs like BERT and GPT [8]. The shift to pretrained language models (PLMs) was pivotal, improving contextually relevant and coherent text generation across applications. Despite advancements, challenges in controlling generated text to include specific words or attributes persist, highlighting the need for innovative control mechanisms [26]. LLMs' tendency to produce factual errors and hallucinations necessitates methods to quantify output uncertainty [27].

CTG methods have evolved to include training-stage approaches, such as retraining and fine-tuning, and inference-stage techniques like prompt engineering and latent space manipulation [24]. Traditional NLP approaches often struggled with expressiveness and constraint satisfaction, necessitating comprehensive methods integrating multiple controllability aspects [6].

The historical context of CTG also involves evolving evaluation methods for NLG systems, challenged by differences between domain-oriented and linguistically motivated ontologies [28]. Traditional methods often lacked capacity to modulate specific attributes' intensity, resulting in ineffective responses [29]. Algorithms struggled to scale effectively with data size, leading to bottlenecks in data retrieval and processing [30].

Recent years have seen a shift towards efficient and adaptable approaches, driven by the need to overcome early methods' limitations and address new challenges. The historical context of NLG has evolved regarding digital deception and detecting deceptive practices [5]. Existing benchmarks for constrained text generation often emphasize fixed constraint types, manageable by state-of-the-art models like GPT-4 [31].

The evolution of CTG and LLMs continues to be driven by the need to enhance model architectures, control mechanisms, and evaluation strategies, aiming for robust and adaptable systems meeting diverse user demands across domains [32].

3 Large Language Models in Text Generation

Large Language Models (LLMs) have revolutionized text generation, driven by their sophisticated architectures and methodologies. This section examines these models, focusing on their structural features and operational capabilities that enhance their performance in producing coherent and contextually relevant narratives. As shown in Figure 2, the hierarchical structure of LLMs is illustrated, highlighting their architecture and capabilities alongside their limitations and recent advancements. This figure categorizes key transformative features, methodologies, and frameworks that contribute to LLM performance. Notably, the limitations section addresses data and output issues, architectural constraints, and content challenges. Furthermore, advancements and breakthroughs are showcased, illustrating model improvements, innovations, and ongoing challenges, which emphasize the evolving landscape of LLMs in controlled text generation.

3.1 Architecture and Capabilities of LLMs

LLMs, notably those based on the Transformer architecture, such as GPT-2, GPT-3, and BERT, have transformed text generation by capturing intricate dependencies through self-attention mechanisms [33]. These models generate coherent narratives using both autoregressive and bidirectional contexts, enhanced by dynamic prompts like CONTROL PREFIXES, which tailor outputs with minimal additional parameters [1].

LLMs integrate diverse methodologies, including the Neural Rule-Execution Tracking Machine (NRETM) for predicate logic-guided generation [12], and the Affective Text Generation Model (ATGM), which optimizes emotional intensity and grammaticality [3]. Tailor exemplifies flexibility by using a single seq2seq model to manage various perturbations via structured control codes [2].

Frameworks like Writing Path use explicit outlines to guide content generation, enhancing text quality [11]. RSA-Control improves attribute management through mutual reasoning between speaker and listener [32]. The integration of external knowledge sources, such as structured knowledge graphs and unstructured bases, enriches text generation by providing additional context and factual accuracy [5].

Advanced methodologies like Plan-to-Text Generation (P2T) separate planning from realization, facilitating a higher-level narrative understanding [11]. The Conditional Variational Auto-Encoder

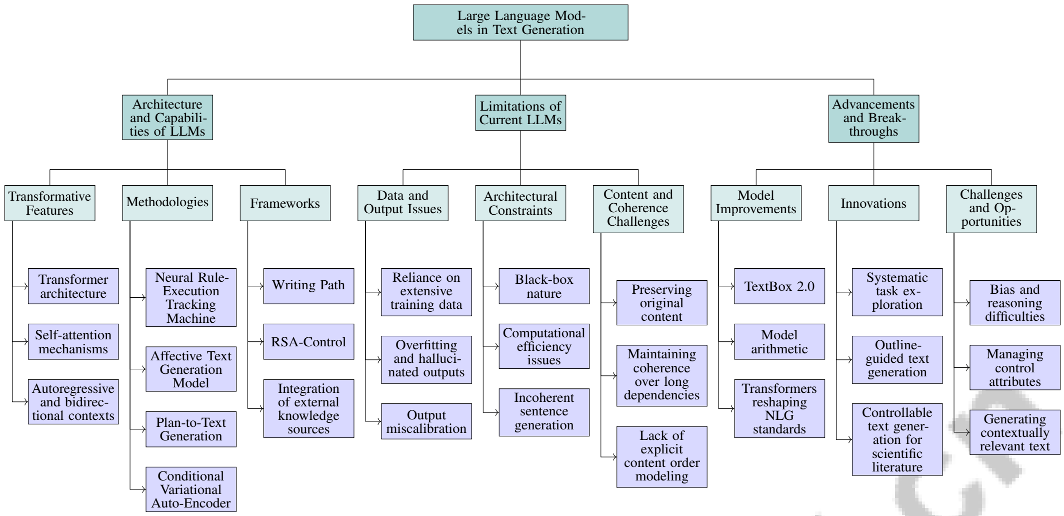

Figure 2: This figure illustrates the hierarchical structure of Large Language Models (LLMs) in text generation, highlighting their architecture and capabilities, limitations, and recent advancements. It categorizes key transformative features, methodologies, and frameworks that enhance LLM performance. The limitations section addresses data and output issues, architectural constraints, and content challenges. Advancements and breakthroughs showcase model improvements, innovations, and ongoing challenges, emphasizing the evolving landscape of LLMs in controlled text generation.

(CVAE) balances accuracy, diversity, and novelty in phrase generation, showcasing adaptability to stylistic and semantic constraints [3].

As illustrated in Figure 4, the architecture and capabilities of LLMs can be categorized into three primary domains: Transformer Models, Methodologies, and Frameworks. Transformer Models include notable examples such as GPT-2, GPT-3, and BERT, which leverage self-attention mechanisms for text generation. Methodologies encompass a variety of approaches, including the NRETM, ATGM, and Tailor, each contributing unique enhancements to text generation. Furthermore, frameworks like Writing Path and RSA-Control, alongside knowledge integration techniques, significantly augment the flexibility and creativity of LLMs in producing coherent and contextually relevant text.

LLMs' architecture and capabilities are marked by diverse methodologies, including knowledge access, dynamic prompt adaptation, and structured writing techniques, enhancing text generation flexibility and creativity. These methods enable LLMs to address task formulation and evaluation challenges, as seen in systems like CUDRT, which improve detection of generated texts, and techniques for controlling attribute intensity [29, 34, 35, 36, 37]. As LLMs evolve, their architecture will offer sophisticated solutions for controlled text generation across applications.

3.2 Limitations of Current LLMs

LLMs face limitations that affect controlled text generation, primarily due to their reliance on extensive training data, which limits multilingual capabilities for less-resourced languages [32]. This reliance can lead to overfitting and hallucinated outputs lacking factual accuracy [27]. Existing benchmarks often fail to consider uncertainty across prompt groups, leading to output miscalibration [39].

The black-box nature of LLMs complicates ensuring generated texts meet control attributes, often requiring significant computational resources for fine-tuning, which can lead to unexpected outputs. Current methods struggle with preserving original content, compromising emotional expressiveness and grammatical correctness. LLMs also face computational efficiency issues, such as low inference efficiency and noise in results due to heuristic scoring functions, affecting performance on complex constructions [21, 40].

Architectural constraints, particularly in maintaining coherence over long dependencies, exacerbate these issues, leading to incoherent sentence generation [22]. The lack of explicit content order

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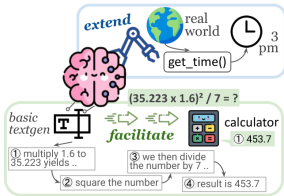
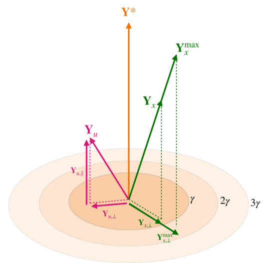
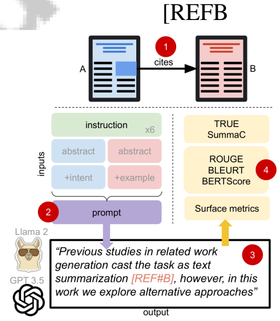


(a) Math Problem Solving with a Brain and Calculator[15]



(b) Vector Representation in a 3D Space[38]



(c) Previous studies in related work generation cast the task as text summarization [REFB ,however, in this work we explore alternative approaches[34]]

Figure 3: Examples of Architecture and Capabilities of LLMs

modeling limits fluency and coherence compared to human writing [8]. These challenges highlight the need for advancements in model architecture, data efficiency, and semantic understanding to enhance LLMs' ability to generate reliable, coherent, and contextually relevant text across applications.

3.3 Advancements and Breakthroughs

Recent advancements in LLMs have significantly impacted text generation, offering more sophisticated control over generated content. TextBox 2.0 exemplifies continuous improvement in model architectures, surpassing original implementations across metrics [41]. Model arithmetic enables precise control by blending multiple models and attributes, aligning outputs with user specifications [42].

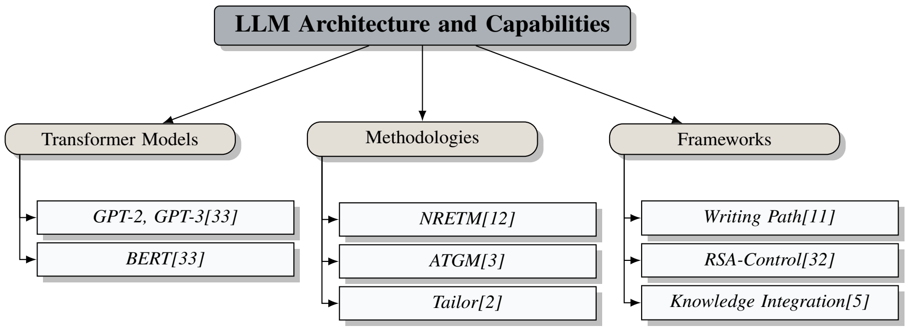


Figure 4: This figure illustrates the architecture and capabilities of large language models (LLMs), highlighting three primary categories: Transformer Models, Methodologies, and Frameworks. Transformer Models include notable models like GPT-2, GPT-3, and BERT, which leverage self-attention mechanisms for text generation. Methodologies encompass various approaches such as the Neural Rule-Execution Tracking Machine (NRETM), Affective Text Generation Model (ATGM), and Tailor, each offering unique enhancements in text generation. Frameworks like Writing Path and RSA-Control, along with knowledge integration techniques, further augment the flexibility and creativity of LLMs in generating coherent and contextually relevant text.

Transformers, the architecture behind many LLMs, have reshaped NLG standards, enabling sophisticated applications across domains [43]. Their ability to capture complex dependencies has advanced narrative fluency and coherence, expanding LLM applicability.

Recent advancements highlight the evolving landscape of NLG, with innovations expanding text generation capabilities. Frameworks for systematic task exploration, such as citation text generation, address task definition and evaluation complexities. Outline-guided text generation enhances content quality and alignment with user intentions, while advancements in controllable text generation for scientific literature introduce structured modulation strategies. A systematic literature review identifies challenges like bias and reasoning difficulties, emphasizing ongoing research and refinement needs [6, 34, 37, 9]. As models improve in managing control attributes and generating contextually relevant text, LLM applications in controlled text generation are poised to expand, offering tailored communication opportunities across domains.

4 Controlled Text Generation Techniques

Controlled text generation is increasingly essential for tailoring language model outputs to specific user-defined constraints and attributes. Table 5 provides a detailed comparison of various controlled text generation techniques, elucidating the methods and strategies employed to enhance language model performance in adhering to specific user-defined constraints. Table 1 presents a detailed categorization of methodologies in controlled text generation, showcasing the range of techniques developed to improve language model performance in adhering to user-defined constraints. This section explores various methodologies that enhance the precision and adaptability of large language models (LLMs) in this context. The subsequent subsection will delve into prompt engineering, a crucial technique for directing LLMs to produce outputs that meet predefined criteria, highlighting its implications and applications.

4.1 Prompt Engineering

Prompt engineering is pivotal in guiding LLMs toward controlled text generation, ensuring outputs align with specific user criteria. This involves crafting input prompts to direct model outputs, maintaining desired attributes or constraints. Table 2 provides a comprehensive comparison of various methods used in prompt engineering to guide large language models in generating controlled text, focusing on different control mechanisms and iterative enhancement techniques. [2] illustrates this through structured control codes that refine LLM outputs. In unsupervised text generation, [21] and [23] employ methods like TGLS and SLUTG, respectively, using heuristic scoring and iterative local edits to enhance prompt engineering's role in text generation.

Category	Feature	Method
Prompt Engineering	Token and Embedding Modifications Guided Output Techniques Structured and Hierarchical Strategies Evaluation and Constraint Satisfaction Output Enhancement Strategies	C-NLG[33] N/A[2] CTG[11] PCAM[10] SLUTG[23]
Language Model Fine-Tuning	Control and Constraints Syntactic Structure Guidance Task and Instruction Integration Search and Refinement	LiFi[1], F-LLM[44], ATGM[3] ITEXP[40] GENPET[13] TGLS[21]
Reinforcement Learning Approaches	Dynamic Modulation Feedback and Adjustment Granular Feedback Mechanisms Feedback-Oriented Strategies Divergence Minimization Model Combination Techniques	RSA[32] PH[45], ENLG[46], RLGF[47] PARGS[48], PMCTG[18], FPT[49], PDRCM[50], ESPT-T5[51] FAST[52] GDC[53] MA[42]
Constraint-Based Methods	Constraint Management Frameworks Structured Planning Techniques Template and Constraint Techniques Probabilistic Control Methods	CFF[54], NRETM[12] GGP[55] TSMH[56] Entmax[57]
Hybrid and Novel Techniques	Factual Integrity and Precision Context Adaptation Strategies Control and Management Strategies Content Coherence Enhancement	SDS[58], TBS[35] TL[59] LiSeCo[60], GT-CTG[61] PLANET[62]

Table 1: This table provides a comprehensive overview of various methodologies employed in controlled text generation. It categorizes the methods into five distinct 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 diversity and complexity of approaches used to enhance language model outputs.

Method Name	**Control Mechanisms**	**Input Modification**	**Iterative Enhancement**
N/A[2]	Control Codes	Input Formats	Local Edits
TGLS[21]	Simulated Annealing	Altering Input Prompts	Iteratively Refine Search
SLUTG[23]	Heuristic Scoring Function	Local Search Edits	Iteratively Proposes Edits

Table 2: Overview of methods employed in prompt engineering for text generation, highlighting control mechanisms, input modifications, and iterative enhancements. The table categorizes approaches such as control codes, simulated annealing, and heuristic scoring functions, illustrating their application in refining large language model outputs.

Prompt engineering extends to preprocessing inputs, modifying token embeddings, and adjusting self-attention mechanisms. [22] highlights the importance of structured plan extraction, emphasizing planning in controlled text generation. Recent advancements like the Prompt Highlighter allow interactive control over text generation, improving quality through guided attention mechanisms [10, 63, 37, 45]. These developments underscore prompt engineering's transformative role in refining LLM capabilities across applications.

4.2 Language Model Fine-Tuning

Fine-tuning is vital for adapting LLMs to controlled text generation, refining pretrained models with additional datasets to meet specific constraints. The TGLS method exemplifies this by coupling search and learning phases to enhance text quality [21]. Fine-tuning integrates auxiliary tasks, allowing content and attribute control by incorporating content inputs into generation. Feedback-aware self-training improves performance by generating counterfactual examples and filtering noisy data, enhancing outputs across tasks like news headline generation and search ad formulation [52, 64].

Optimizing LLMs through fine-tuning involves integrating instructions and labeled examples, enhancing data efficiency. Training attribute classifiers on limited labeled data allows deriving control codes applicable to larger volumes of unlabeled data, enabling precise control over attributes like sentiment and writing style [1, 65, 52, 66, 67]. Fine-tuning is crucial for adapting LLMs to controlled text generation, enabling outputs that meet specific constraints across applications [29, 68, 69, 34].

4.3 Reinforcement Learning Approaches

Reinforcement learning (RL) enhances controlled text generation by providing a framework for models to learn optimal strategies through feedback. RL's potential is demonstrated in engaging summaries generated using web crawling, showcasing its capacity for synthesizing coherent content

[46]. The RLGF method surpasses traditional RL techniques, emphasizing guided feedback's effectiveness in fine-tuning LLMs [47]. The RSA-Control method introduces dynamic control strength modulation, enhancing text generation quality [32].

The Prompt Highlighter approach guides autoregressive generation through adjusted attention scores, aligning outputs with user needs [45]. Recent advancements address challenges like sparse rewards in unsupervised tasks, improving performance with dense reward mechanisms and novel algorithms like TOLE [70, 71]. As RL techniques evolve, they are set to enhance LLM adaptability and precision in controlled text generation.

4.4 Constraint-Based Methods

Method Name	Control Mechanisms	Optimization Techniques	Adaptability Features
GGP[55]	Explicit Control	Optimization Problem	Structured Approach
CFF[54]	Constraint Programming	Combinatorial Optimization Problem	Classical Constraints
NRETM[12]	Predicate Logic	Dynamic Tracking Mechanism	Flexible Application
Entmax[57]	Sampling Techniques	Entmax Transformation	Adaptively Change Context

Table 3: This table provides a comparative analysis of various constraint-based methods used in language model outputs, focusing on their control mechanisms, optimization techniques, and adaptability features. It highlights the distinct approaches and methodologies employed by each method to maintain content quality and relevance in complex applications.

Constraint-based methods apply specific rules to guide language model outputs, ensuring adherence to predefined attributes by formulating the decoding process as an optimization problem. These methods maintain content quality and relevance, particularly in complex applications requiring precise control [6, 72]. Table 3 presents a detailed comparison of constraint-based methods, illustrating their diverse control mechanisms, optimization techniques, and adaptability features in the context of language model outputs. The GGP method exemplifies explicit control by creating detailed plans from key phrases [55]. Another approach transforms constrained text generation into a combinatorial optimization problem, employing constraint programming for managing complex interactions [54].

COLLIE introduces a grammar-based framework for specifying compositional constraints, enhancing language models' adaptability [31]. NRETM employs a dynamic tracking mechanism for managing logical constraints [12]. Entmax sampling introduces a sparse probability distribution for nuanced control over text generation [57]. These methods address challenges like bias and hallucinations, enhancing accuracy and reliability across applications [73, 66, 9, 74].

4.5 Hybrid and Novel Techniques

Method Name	Method Integration	Control Mechanisms	Application Contexts
SDS[58]	-	Semantic Drift Scores	Educational Tools
TBS[35]	Search Trees	Confidence Scores	Creative Text Generation
LiSeCo[60]	Integrate Probing Classifiers	Control-theoretic Intervention	Toxicity Avoidance Tasks
GT-CTG[61]	Nash Equilibrium Feedback	Strategic Prompt Interventions	Real-world Applications
PLANET[62]	Dynamic Content Planning	Semantic Guidance Representations	Argument Generation Reddit

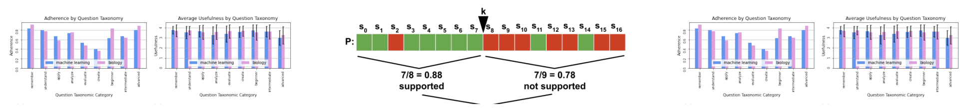
Table 4: Overview of hybrid and novel techniques in language model integration, detailing various methods, their integration strategies, control mechanisms, and application contexts. This table highlights the diversity of approaches, from semantic drift scores in educational tools to strategic prompt interventions in real-world applications, underscoring the advancement in controlled text generation.

Hybrid and novel techniques integrate various methodologies to enhance language models' precision and flexibility. A semantic drift score quantifies factual integrity, crucial for maintaining content accuracy [58]. Combining search trees with confidence-based sampling represents a hybrid technique for controlled text generation [35]. LiSeCo introduces control-theoretic intervention for systematic output management [60].

Systematic mixing of representation levels offers a flexible text generation process [75]. Implementing Nash equilibrium optimizes the balance between directive and narrative prompts [61]. PLANET dynamically integrates content planning and surface realization, enhancing coherence and relevance [62].

Recent advancements include a schema for generating scientific literature, strategies for structural coherence in long-form text, and a systematic review of text generation tasks, highlighting challenges and solutions [6, 7, 9]. As these techniques develop, they will enhance generated text quality and offer new opportunities for tailored communication.

Table 4 presents a comprehensive summary of hybrid and novel techniques employed to enhance the precision and flexibility of language models, showcasing the integration of diverse methodologies and their application in various contexts.



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

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

(c) Adherence and Average Usefulness by Question Taxonomy[17]

Figure 5: Examples of Hybrid and Novel Techniques

As shown in Figure 5, hybrid and novel techniques enhance controlled text generation quality and relevance. Visual aids such as bar charts and segmented lines illustrate these techniques' potential in educational and decision-making contexts [19, 58, 17].

Feature	Prompt Engineering	Language Model Fine-Tuning	Reinforcement Learning Approaches
Control Mechanism	Input Prompts	Auxiliary Tasks	Feedback Learning
Optimization Technique	Iterative Enhancement	Feedback-aware Self-training	Dense Rewards
Adaptability	High	High	Moderate

Table 5: This table provides a comparative analysis of three prominent methodologies for controlled text generation: prompt engineering, language model fine-tuning, and reinforcement learning approaches. It highlights the distinct control mechanisms, optimization techniques, and adaptability levels associated with each method, offering insights into their respective strengths and applications in enhancing language model outputs.

5 Applications of Controlled Text Generation

5.1 Education

Controlled text generation is revolutionizing education by creating tailored content that aligns with pedagogical goals and learning standards. This technology enables the generation of educational materials that are contextually relevant and cater to diverse learning styles. For instance, GeneUS automates user story creation in software engineering, showcasing practical applications in educational settings [76].

Controlling text attributes such as sentiment, formality, and toxicity is crucial for producing engaging educational content. The Locate and Edit (LE) framework effectively manages these attributes, ensuring content suitability for various educational environments [77]. This capability is vital for producing materials that are informative and sensitive to learners' emotional and cultural needs.

The adaptability of controlled text generation is further demonstrated by the Affective Text Generation Model (ATGM), applicable in dialogue systems and therapeutic chatbots, providing personalized learning experiences in educational and mental health contexts [3]. This highlights the versatility of controlled text generation in enhancing educational resource quality and accessibility.

Datasets like COLLIE-v1, derived from real-world sources, establish a robust foundation for developing educational content that adheres to specific constraints, ensuring accuracy and relevance [31]. This approach is instrumental in producing high-quality educational materials that address diverse learner needs.

As techniques involving large language models (LLMs) advance, they promise to significantly improve educational methodologies and learning outcomes. By generating high-quality, personalized educational content—such as tailored questions aligned with Bloom's taxonomy—these tools can alleviate cognitive load on teachers and foster more effective learning experiences globally, thereby elevating the overall quality of educational resources [17, 66, 19, 9, 37].

5.2 Healthcare

Controlled text generation significantly enhances healthcare by producing contextually accurate and personalized content, improving patient communication, medical documentation, and decision support systems. These advancements facilitate structured outputs that improve information clarity and relevance for patients and professionals [6, 7, 69, 9].

A key application is automating medical report generation. By leveraging LLMs with fine-tuning techniques, healthcare providers can produce detailed reports that adhere to clinical protocols, optimizing documentation and alleviating cognitive burdens on professionals, thereby enhancing healthcare delivery [66, 78, 9, 37].

Controlled text generation also aids in developing patient education materials tailored to individual needs and health literacy levels. By manipulating attributes such as readability, tone, and sentiment, it enhances information accessibility and comprehension, fostering greater patient engagement and adherence to treatment plans [29, 65].

In mental health, therapeutic chatbots and virtual assistants use emotion-conditioned text generation to provide personalized support, delivering empathetic interactions aligned with users' emotional states [6, 79, 3, 29].

Moreover, controlled text generation extends to clinical decision support systems, generating evidence-based recommendations that assist clinicians in making informed decisions. By integrating structured and unstructured data, these techniques provide in-depth insights that enhance clinical workflows and patient outcomes, addressing challenges of bias and interpretability [6, 7, 9].

As advancements in technologies like LLMs progress, they are set to improve healthcare delivery and patient care by enabling more accurate, comprehensive, and verifiable reporting, addressing complex information needs, and enhancing communication quality in medical contexts [6, 78, 9].

5.3 Content Creation and Storytelling

Controlled text generation is pivotal in content creation and storytelling, producing narratives that adhere to specific constraints while maintaining coherence and engagement. The GGP method demonstrates superior performance in generating coherent long texts, emphasizing structured planning in narrative generation [55].

The PHVM framework is applicable in tasks like advertising text and recipe generation, highlighting the versatility of controlled text generation in producing diverse content that meets user-defined criteria [80]. Furthermore, the LiFi framework showcases stylistic novel writing, demonstrating the potential of controlled text generation in crafting narratives that align with specific stylistic requirements [1].

The TGLS framework is applicable in generating paraphrases and formalizing text, ensuring that generated content is engaging and relevant across different contexts [21]. The search and learning approach for unsupervised text generation has achieved significant improvements, demonstrating high-quality text generation without extensive labeled datasets [23].

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

Recent advancements, such as sequentially controlled text generation, demonstrate the ability to impose structural coherence on longer texts, improving control accuracy and coherence to levels approaching human writing. The development of a comprehensive schema for controllable text generation in scientific literature highlights various modulation strategies, paving the way for new architectures and empirical comparisons to refine these methods [6, 7].

5.4 Business Process Management

Controlled text generation significantly impacts Business Process Management (BPM) by enhancing the efficiency and accuracy of information extraction from unstructured textual documents. Large Language Models (LLMs) are increasingly utilized for complex BPM tasks, leveraging their ability to process and generate contextually relevant text [81]. These models excel at mining imperative and declarative process models, crucial for optimizing business workflows.

LLMs play a pivotal role in assessing task suitability for robotic process automation (RPA), streamlining the integration of RPA solutions and enhancing overall process efficiency [81]. This capability is valuable in automating repetitive, rule-based tasks, leading to significant cost savings and productivity improvements.

Controlled text generation extends to developing intelligent systems that support decision-making processes. By analyzing vast amounts of textual data, LLMs facilitate informed decision-making, allowing businesses to adapt quickly to market dynamics and operational challenges. Systematic exploration of task inputs and evaluation metrics enhances the effectiveness of LLMs in generating actionable insights, leading to more agile strategies in a rapidly changing environment [34, 36]. 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 transformed media and entertainment by providing advanced solutions for content creation, curation, and personalization. Techniques such as sequentially controlled text generation enhance structural coherence and topical relevance, while unsupervised constrained text generation enables high-quality content production without supervised data [6, 7, 18, 9]. The ability of LLMs to generate high-quality, contextually relevant text has reshaped media content production and consumption, allowing for personalized narratives and interactive experiences that engage audiences effectively.

In the media landscape, controlled text generation automates news article creation, ensuring adherence to editorial guidelines and maintaining structural coherence. Recent advancements, such as sequentially controlled text generation, improve the grammaticality and coherence of generated texts, achieving levels comparable to human writing. Techniques like plug-and-play decoding refine this process, enabling precise control over word inclusion to meet editorial standards while ensuring content fluency and diversity [6, 7, 26]. This capability is valuable for timely reporting, enabling the generation of coherent and accurate articles that maintain the publication's voice. Controlled text generation also enhances media content personalization, tailoring articles and recommendations to individual preferences, thereby increasing reader engagement.

The entertainment industry benefits from controlled text generation 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 significantly enhances immersive quality, providing users with agency that traditional static narratives lack. Such methodologies allow for tailored experiences that enrich engagement and satisfaction within interactive entertainment mediums [82, 37, 61].

Moreover, controlled text generation techniques have advanced the creation of sophisticated virtual characters and chatbots capable of engaging users in natural, context-aware conversations. Techniques like sequentially controlled text generation and plug-and-play decoding ensure that dialogues maintain fluency and adhere to specific topics, enhancing user interaction. These advancements facilitate the development of chatbots that adapt responses based on user input, creating meaningful exchanges crucial for lifelike characters in video games and virtual environments [6, 26, 83, 7, 84].

The integration of controlled text generation into media and entertainment significantly enhances content production efficiency through advanced modulation strategies and structural awareness techniques while fostering innovative avenues for creative expression and interactive audience engagement. As these technologies continue to evolve, they are poised to redefine the boundaries of media and entertainment, offering innovative solutions that enhance content quality and personalization across various platforms.

6 Challenges and Limitations

The exploration of challenges and limitations in controlled text generation (CTG) reveals a complex interplay of ethical, computational, and resource-related dimensions. Ethical implications, particularly regarding biases and misuse potential, necessitate a comprehensive examination of the responsibilities accompanying the deployment of these technologies. Computational demands associated with fine-tuning large language models (LLMs) and resource constraints in various contexts present significant barriers to scalability and effectiveness. This section begins with an in-depth analysis of bias, ethical concerns, and misuse potential.

6.1 Bias, Ethical Concerns, and Misuse Potential

CTG raises critical ethical challenges, primarily due to biases inherent in LLMs and their potential for misuse. These models often reflect and amplify biases present in training data, raising concerns about perpetuating stereotypes and generating biased content [13]. The limited interpretability of deep neural networks complicates efforts to ensure quality while adhering to constraints [3]. Misuse potential, including the creation of harmful content, poses significant ethical risks and impacts user experience [22]. Ethical considerations extend to the reliability and trustworthiness of CTG systems, encompassing data bias, fairness, privacy concerns, and the risk of generating misleading information [78, 5, 20, 9]. Invalid plans generated by LLM-based agents can lead to errors in task execution, impacting user trust. The black-box nature of existing models often results in unreliable adherence to constraints, especially under complex logical conditions. Addressing these concerns requires robust detection systems and guidelines to mitigate risks associated with bias, misinformation, and privacy violations. Continuous research and development are essential to enhance awareness and tackle evolving security threats [5, 9, 20]. Furthermore, automated extraction and filtering processes can introduce quality issues, affecting the reliability of generated content. To ensure responsible deployment, it is vital to develop robust evaluation metrics and strategies that enhance transparency and interpretability while producing reliable outputs [6, 5, 65, 20, 9]. Implementing safeguards and fostering awareness will allow for harnessing the benefits of CTG while mitigating associated risks.

6.2 Computational and Resource Limitations

CTG faces significant computational and resource limitations that hinder scalability and effectiveness across applications. A primary constraint is the substantial computational resources required for fine-tuning LLMs, which can be especially prohibitive in resource-constrained environments [76]. The complexity of selecting and optimizing transformation networks further complicates the process, as maintaining the integrity of representations is crucial [40]. The non-deterministic nature of LLM outputs requires further translation into formalized languages for specific applications, adding to the computational burden [10]. Current methods struggle to manage multiple subjects efficiently without retraining, and focused prefix tuning (FPT) methods, while offering improved control, incur higher time costs compared to simpler techniques [1]. The reliance on structured training data poses additional challenges, as methods proposed by [21] depend on data availability, which may not always be accessible. The need for manual logical forms for content selection limits scalability, making large-scale applications impractical [76]. Token limits in text encoding can lead to omissions and inaccuracies when processing long prompts, affecting output quality [2]. Furthermore, the structure of input data in certain methods may hinder generalization to more complex datasets [23]. The computational inefficiency of Natural Language Inference (NLI) strategies can slow down generation, particularly when multiple iterations are needed to satisfy NLI checks [33]. Additionally, the quality of guide policies in Reinforcement Learning with Guided Feedback (RLGF) methods may not always be optimal, impacting overall performance [10]. The additional computational overhead introduced by extra decoding branches required for highlight mechanisms exemplifies the resource constraints faced in CTG [1]. Addressing these computational and resource limitations is essential for advancing CTG, as they hinder the development of effective architectures and modulation strategies that enhance coherence, grammaticality, and topical relevance across various tasks such as summarization, translation, and question answering [6, 7, 85, 9]. Developing more efficient models and methodologies will expand the applicability of CTG across domains, meeting the growing demands for high-quality, contextually relevant text.

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6.3 Control Mechanisms and Attribute Management

The implementation of control mechanisms and effective attribute management in CTG presents challenges, particularly as text generation technologies become more accessible and sophisticated. While these advancements expand potential applications, they also increase the risk of harmful outcomes if control mechanisms are not robustly implemented [14]. A core challenge is generating contextually appropriate cues without extensive manual intervention, as existing methods often fall short [82]. Controlling the generation of explanations in specified formats is another significant obstacle, leading to omissions and ambiguities in output. This highlights the need for precise control over generated text to ensure clarity and coherence [86]. 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 in the PHVM framework, hold promise for addressing these challenges by modeling input data and maintaining coherence across sentences [80]. However, even advanced planning mechanisms may struggle with very complex narratives, indicating a need for further advancements in control mechanisms and attribute management [55]. The challenges in implementing control mechanisms and managing attributes necessitate ongoing research to enhance the precision and reliability of language models. By addressing nine prominent challenges identified in recent literature—such as bias, reasoning, and hallucinations—researchers can significantly improve the quality and coherence of generated text, ensuring outputs meet user-defined constraints across various applications, including open-ended text generation, summarization, translation, paraphrasing, and question answering. Integrating diverse forms of knowledge into generation models can also enhance performance in real-world scenarios [85, 9].

6.4 Long Text Generation and Coherence

Generating coherent long texts with controlled attributes presents significant challenges due to the complexity of maintaining narrative coherence and logical progression over extended lengths. Current models often struggle with content selection and ordering, which are crucial for producing coherent long-form narratives [62]. The lack of explicit mechanisms to manage event transitions and maintain thematic consistency can result in disjointed outputs, undermining text quality. A primary challenge in long text generation is effective planning of event transitions, essential for ensuring logical flow from one event to the next. The absence of such planning can lead to abrupt transitions that disrupt reader engagement and comprehension [87]. Innovative approaches are needed to explicitly arrange events within the text, enhancing coherence and readability. Moreover, managing multiple attributes simultaneously—such as style, tone, and factual consistency—adds complexity to long text generation. Models must generate contextually relevant and logically ordered content while complying with user-defined constraints, addressing challenges like bias, coherence, and reasoning [6, 9]. Balancing narrative coherence with attribute requirements remains a challenge for current models. Advancements in content planning and event transition management are crucial for improving long text generation quality and coherence. Developing sophisticated models that effectively organize and integrate narrative elements will enhance output alignment with user expectations and maintain thematic integrity across applications, including academic writing, news articles, and creative storytelling. Structured approaches, such as outline-guided frameworks and planning techniques, have shown promise in enhancing relevance, organization, and verifiability of generated content. Incorporating diverse knowledge beyond input text can further bolster model performance, addressing common challenges in coherence and reasoning [88, 85, 9, 37].

7 Future Directions

7.1 Enhancements in Model Architecture and Training

Advancing model architecture and training methods is crucial for overcoming limitations in controlled text generation (CTG). Future research should focus on automating effective task descriptions and enhancing contextual understanding, particularly in complex emotional scenarios. By integrating diverse knowledge sources and aggregation techniques, coherence can be improved, redundancy reduced, and quality elevated across applications such as summarization, translation, and question answering [85, 89, 9]. Enhancements seen in models like LiFi suggest promising architectural refinements [1], while refining control code design and semantic representations, as in Tailor, can offer precise content control [2].

Efforts should also target improving search algorithms, noise robustness, and developing efficient search techniques and scoring functions. Expanding benchmarks with diverse datasets and evaluation metrics will enhance model applicability across language generation tasks [22]. Addressing challenges in knowledge-enhanced text generation, such as integrating diverse knowledge forms and enhancing semantic validity through automated grammar checking, will be pivotal for advancing language technologies. This will lead to sophisticated, reliable, and adaptable solutions in automated content generation, educational technology, and customer service, improving AI-generated text accuracy and contextual relevance [6, 85, 9, 90].

7.2 Advanced Control Mechanisms

Enhancing control mechanisms in CTG is vital for improving precision and adaptability. These mechanisms enable models to generate text that aligns with user-defined constraints, enhancing output quality and relevance. Reinforcement learning offers an innovative approach, allowing iterative refinement based on feedback to ensure adherence to desired attributes [46]. Control-theoretic interventions, such as those in LiSeCo, demonstrate the potential for guiding outputs with minimal computational overhead [60]. Nash equilibrium strategies provide a framework for balancing directive and narrative prompts, optimizing content quality through stable strategy profiles [61].

Dynamic prompt adaptation, exemplified by RSA-Control, showcases the potential of advanced mechanisms to adjust control strength based on contextual needs, enhancing model adaptability [32]. This progress introduces innovative solutions that align outputs with user-defined attributes, improving control accuracy, grammaticality, coherence, and topical relevance. Future research aims to empirically compare these methods to elucidate their strengths and applications [6, 7].

7.3 Applications and Domain-Specific Adaptations

Future research in CTG will explore diverse applications and domain-specific adaptations, enhancing language model versatility and effectiveness. In education, integrating generated questions into classrooms and comparing their efficacy with human-generated questions can refine pedagogical approaches [84]. Extending frameworks like STANDARDIZE to other languages and educational contexts can yield more inclusive learning tools. The exploration of multilingual generation using universal POS tags presents promising avenues for real-world data-to-text applications, potentially bridging language gaps in educational and professional settings.

Investigating benchmarks across languages and examining non-causal models in NLG tasks is crucial for improving adaptability and robustness [91, 92, 9]. Leveraging frameworks like NADO can help mitigate biases, promoting equitable content generation. Enhancing referring expression generation and developing robust methodologies for addressing unseen entities can significantly elevate text generation quality [85, 93, 94, 95, 9].

In business process management, future research should explore LLM applications in additional BPM tasks and improve prompt designs for enhanced output quality [81]. Extending methods like MAGIC to modalities beyond images, such as audio and video, could enhance multimodal text generation capabilities [96]. Expanding text generation libraries with more tasks and improving training efficiency are critical for broadening language model applicability. Integrating structured frameworks in cross-lingual contexts and enhancing citation intents' clarity can elevate academic writing standards, promoting thorough scholarly communication while leveraging LLMs to align content with user intentions [6, 34, 37, 9].

7.4 Ethical and Societal Implications

Advancements in CTG bring significant ethical and societal implications requiring careful consideration. A primary concern is the potential for models to perpetuate biases, leading to harmful content. Robust model development and bias detection mechanisms are essential to mitigate these risks and ensure ethical text generation [20]. Privacy-preserving practices are critical, particularly due to the sensitive nature of processed data. Compliance with regulatory standards is vital to protect

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user privacy and maintain trust. Parameter-efficient models can further mitigate risks by reducing computational footprints and potential exposure of sensitive information [20].

The societal implications extend to potential misuse, such as generating misleading content. This underscores the need for comprehensive regulatory frameworks governing CTG technologies' ethical application. Such frameworks are essential to ensure advancements enhance natural language processing capabilities while addressing bias, privacy, and misuse challenges, fostering beneficial societal outcomes [6, 85, 18, 9]. Integrating ethical guidelines and transparency in model development can promote responsible use and foster public trust.

Ongoing attention from researchers, developers, and policymakers is necessary to address CTG's ethical and societal implications. By emphasizing ethical considerations and establishing comprehensive safeguards, it is feasible to leverage CTG technologies' advantages while mitigating associated risks such as data bias, misinformation, and privacy violations. This approach ensures these advanced systems are utilized responsibly, contributing positively to society [97, 18, 5, 20].

8 Conclusion

The survey underscores the transformative role of controlled text generation (CTG) within natural language processing (NLP), particularly through the advancements facilitated by transformer-based pre-trained language models (PLMs) that enhance text generation capabilities. Despite these advancements, challenges persist in achieving fine-grained control and maintaining the quality of generated text [8]. The SCTG method has demonstrated significant improvements in structural coherence and overall text quality, approaching human-level performance, thus highlighting the potential of innovative methodologies in advancing CTG [7].

The superior performance of CriticControl across various tasks emphasizes the importance of ongoing research in refining CTG techniques to produce coherent and controlled text [98]. The architecture of PLMs plays a crucial role in optimizing text generation outcomes, necessitating further exploration to enhance the applicability and effectiveness of these models [94]. However, evaluations indicate that while large language models (LLMs) excel in generating rationales and adhering to broad control signals, they encounter significant challenges with precise, hard constraints [99].

There is a clear need for robust evaluation frameworks that integrate human judgment with automatic metrics, as these frameworks can significantly improve the accuracy and reliability of CTG assessments [100]. As the field advances, the development of more sophisticated models and evaluation methods will be essential to overcoming existing limitations and expanding the capabilities of CTG. This ongoing research and development are crucial for ensuring that CTG continues to evolve and make a positive impact on the broader field of NLP.

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