Why is constrained neural language generation particularly challenging?

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Abstract—Recent advances in deep neural language models combined with the capacity of large scale datasets have accelerated the development of natural language generation systems that produce fluent and coherent texts (to various degrees of success) in a multitude of tasks and application contexts. However, controlling the output of these models for desired user and task needs is still an open challenge. This is crucial not only to customizing the content and style of the generated language, but also to their safe and reliable deployment in the real world. We present an extensive survey on the emerging topic of constrained neural language generation in which we formally define and categorize the problems of natural language generation by distinguishing between conditions and constraints (the latter being testable conditions on the output text instead of the input), present constrained text generation tasks, and review existing methods and evaluation metrics for constrained text generation. Our aim is to highlight recent progress and trends in this emerging field, informing on the most promising directions and limitations towards advancing the state-of-the-art of constrained neural language generation research.

Index Terms—neural networks, text generation, constraints.

I. INTRODUCTION

Recent advances in the field of natural language generation (NLG)\cite{36} have resulted in models able to produce realistic, coherent, and fluent texts in a multitude of natural language processing tasks. Powerful large scale language models can be readily used to perform unconditional language generation, however these models provide little control over attributes of the generated texts. Unlike conventional methods which were able to provide fine-grained control over many aspects of the system output including incorporating domain-specific dictionaries, terminology or certain words in the generated texts, neural text generation problem. We then survey approaches, presenting examples that represent instantiations of the constrained conditions and constraints in text generative models has numerous applications in many natural language processing areas, including dialogue systems, machine translation, question answering, text summarization, text simplification, image captioning, etc. Unquestionably, constrained text generation is important in many real-world applications, but compared to other instances of natural language generation, constrained text generation using neural networks remains an open challenge.

We identify the following reasons that explain why constrained neural text generation represents a much harder problem compared to other instances of neural text generation: i) lack of model expressiveness: current models are not expressive enough to incorporate arbitrary constraints, defined as testable conditions on the output text, into the objective function at training time; ii) lack of suitable evaluation metrics: while one can verify whether an output satisfies a constraint or not, it is usually hard to measure to what extent an output satisfies a constraint, and it is even harder to jointly evaluate this with other properties of the generated text (such as relevance or coherence); iii) difficulty in constrained optimization: even if constraints can be expressed and added to the objective function, they are usually non-differentiable, especially at the token level. This is bad as most methods model and generate text as a sequence of tokens; iv) lack of constrained text generation datasets that are diverse and representative enough of the variety of practical constraints.

For example, commonly used sequential text generation methods and architectures assume a rigid modeling of the output sequence based on an ordering of words, in which tokens are generated progressively one at a time in a standard left-to-right manner\cite{15}. Such autoregressive models cannot easily express constraints at arbitrary positions in the generated sequence or satisfy constraints involving multiple input objects. In addition to these issues, it is generally more challenging to incorporate multiple and heterogeneous constraints, which conform to given rules, topics, sentiments, lexical constraints, or pre-defined stylistic and content attributes.

Our work focuses on the emerging problem of neural natural language generation with constraints. We first define the problem and differentiate between the ambiguous use of conditions and constraints in natural language generation, including examples that represent instantiations of the constrained neural text generation problem. We then survey approaches, learning methodologies and model architectures employed for
generating texts with desirable attributes, and corresponding evaluation metrics. We conclude with open research problems and limitations of current models. The scope of our work is draw clear boundaries between the confusing terminology used in the natural language generation literature, highlight the main approaches and discuss how they suffer from the general challenges of constrained text generation, and serve as an informative guide and an advocate for solving these general challenges and advancing meaningful, useful, and safe constrained NLG research.

II. PROBLEM DEFINITIONS

We formally define the problem of natural language generation, accounting for context, conditions, and constraints placed on text generative models. First, we aim to articulate the key difference between condition and constraint since the distinction between these concepts is rather blurred in the natural language processing literature. Given a text generation task defined as \( g(X) \rightarrow X' \), we define condition as a testable statement of the input \( X \), and constraint as a testable statement of the output \( X' \).

Accounting for the distinction above, we divide the text generation problem into three categories: i) generic or free-text generation which we present in Section II-A ii) conditional text generation which we introduce in Section II-B and iii) constrained text generation which we outline in Section II-C.

The focus of our work is on the particular problem of constrained text-to-text generation, leaving aside text generation tasks from other types of inputs such as data-to-text generation or image-to-text generation which are conditional in nature according to our definitions.

A. Generic / Free-Text Generation

The problem of generic text generation considers the intrinsic history of words generated until the current timestep in the sequence as context, and does not place any external user-defined conditions or constraints on the model output.

Given a discrete sequence of text tokens \( x = (x_1, x_2, \ldots, x_n) \) as input where each \( x_i \) is drawn from a fixed set of symbols, generic text generation aims to learn the unconditional probability distribution \( p(x) \) of sequence \( x \). This distribution can be auto-regressively factorized using the chain rule of probability \([7]\) into a product of conditional probabilities \( p(x) = \prod_{i=1}^{n} p(x_i|x_{<i}) \) to perform density estimation and generation of language data. When \( p(x) \) is modeled by a neural network with parameters \( \theta \), the model minimizes the negative log-likelihood loss function accounting for the attribute code \( c \): \( \mathcal{L}(D) = -\sum_{k=1}^{D} \log \theta(\mathbf{x}_k|\mathbf{x}_{<k}, c^k) \). Besides generation, conditional models can also be used as generative classifiers to compute \( p(c|x_{<i}) \) by applying Bayes rule.

B. Conditional Text Generation

Conditional text generation manipulates attributes of the generated content depending on specific contexts or user needs, and allows the data generation process to focus on specific modes of the data. Conditioning the generative model on additional information makes it possible to generate texts which satisfy given input conditions and meet desired attributes. In the literature, conditional text generation is sometimes referred to as context-dependent text generation. While the word context may carry different semantics for different readers, in this survey we consider as context only attributes which are inherently external to the model itself; model intrinsic attributes such as for example, the history of past generated words, is already included in the formulation of generic text generation. For example, context attributes used for conditioning generated texts are the source sentence in machine translation, the conversational history in dialogue systems, the input document in text summarization and text simplification, the input question in question answering systems, or contextual information such as product, time, and location in review generation.

Conditional text generation models add a contextual variable or attribute code \( c \) to the probabilistic model \( p(x|c) \), which can be auto-regressively decomposed using the chain rule of probability \( p(x|c) = \prod_{i=1}^{n} p(x_i|x_{<i}, c) \). When \( p(x|c) \) is modeled by a neural network with parameters \( \theta \), the model minimizes the negative log-likelihood loss function accounting for the attribute code \( c \): \( \mathcal{L}(D) = -\sum_{k=1}^{D} \log \theta(\mathbf{x}_k|\mathbf{x}_{<k}, c^k) \).

C. Constrained Text Generation

The problem of constrained text generation is focusing on generating coherent and logical texts that do (not) cover lexical concepts (for eg., pre-defined nouns, verbs, entities, phrases or sentence fragments) desired to be (not) present in the output, as well as generate outputs that abide to specific format, semantic, syntactic or utility rules to reflect the particular interests of the system user. Constraints impose restrictions on the generative model that must be satisfied by any solution to the optimization problem and their fulfillment can be tested accordingly. In the literature the distinction between conditional, controlled, and constrained text generation is not clearly defined, and these terms are often used interchangeably. In fact, the first work
that proposed generating constrained text is actually referring to the task as “controlled” generation \[55\]. In what follows we formally define the problem of constrained text generation.

Let us consider we are (optionally) given an unordered or ordered set of \(n\) concepts \(x = \{c_1, c_2, \ldots, c_n\} \in \mathcal{X}\), where \(\mathcal{X}\) denotes the space of all concepts, and \(c_i \in C\) is a concept belonging to the concept vocabulary \(C\). In addition, let us assume we are also (optionally) given a set of \(m\) rules \(y = \{y_1, y_2, \ldots, y_m\} \in \mathcal{Y}\), with \(y_i \in \mathcal{R}\), where \(\mathcal{R}\) denotes the space of all rules, and each \(y_i\) is a text generation constraint expressed in logical form. We formulate constrained text generation as learning the structured predictive function \(f: \mathcal{X} \cup \mathcal{Y} \rightarrow \mathcal{Z}\), where \(\mathcal{X} \cup \mathcal{Y} \neq \emptyset\) which maps a set of concepts and/ or constraint rules to a generated sentence. Therefore, constrained text generation methods impose constraints on the generated sentences and produce output in the form of grammatical sentence \(z \in \mathcal{Z}\) which contains all concepts present in \(x\) and all constraint rules specified in \(y\).

The probability \(p(z|f)\) can still be modeled autoregressively \(p(z|f) = \prod_{i=1}^{n} p(z_i|z_{<i}, f)\); when \(p(z|f)\) is modeled by a neural network with parameters \(\theta\), the negative log likelihood function can be minimized while leveraging \(f\) for constraint satisfaction \(L(D) = -\sum_{k=1}^{D} \log p_{\theta}(z_{<i}^{f}|z_{>i}^{f}, f)\).

The matching function \(f\) manipulates the probability distribution and indicates to which extent the constraints are satisfied. In the literature, constrained text generation methods can be either i) Soft-constrained (priming), when the matching function \(f\) is a soft measure of semantic similarity and only requires the generated sentences to be semantically related to the given constraints, or ii) Hard-constrained, when the matching function \(f\) is a binary indicator which rules out the possibility of generating infeasible sentences that do not meet the given constraints. Hard-constrained text generation is notably a more challenging task compared to soft-constrained text generation, and it requires designing specialized approaches and architectures to ensure the constraints in the output sentence. In contrast, soft-constrained text generation models are usually easier to design, e.g., with the use of existing copy and attention mechanisms for soft enforcing constraints and annotated keyword-text pairs; nevertheless, some of these soft constraints are likely to be lost during generation, especially if multiple weakly correlated (lexical) constraints must be included \[168\].

Compared to generic text generation which assumes no conditions on input or output other than existing context, and compared to conditional text generation which places conditions on the input which can be considered at training time, constrained text generation places conditions on the output which is a considerably more difficult and challenging problem to solve. Unlike input conditions, output conditions cannot be considered at training time and their satisfaction is assessed after training has completed by sampling and inspecting the generated outputs. In addition, standard sequence generation architectures are not designed to easily accommodate or incorporate output constraints. Given the model structure itself cannot express output conditions, it becomes challenging to evaluate the extent to which constraints are satisfied by a model, objectively compare and contrast the performance of different models, and measure overall success to inform on progress in constrained natural language generation. Due to these limitations, current methods proposed to address constrained text generation are neither satisfactory nor sufficient. The main machine learning challenge is that it is hard to evaluate the objective function for constrained text generation, and very few works have approached the problem from the prism of editing the objective function to incorporate constraints at training time. Even if constraints were to be added to the objective function itself, constrained optimization would be another challenge. In general, reinforcement learning approaches are used in the context of text generation to optimize non-differentiable reward functions computed at the token level, for eg., BLEU in machine translation or ROUGE in text summarization. However, optimizing such automatic measures that focus on local n-gram patterns often results in deteriorated textual outputs despite increased automatic scores \[9\], \[116\]. Moreover, applying reinforcement learning to text generation at the word level leads to difficulty in proper temporal credit assignment for long-term textual rewards \[128\].

Given that the environment provides only delayed rewards as the agent executes a sequence of actions, it is impossible to know whether the agent succeeds in achieving a task until the end of the episode, at which point the agent needs to determine which of the actions in the sequence are to be credited with producing the resulting reward \[24\]. Adding constraints on top of existing reinforcement learning issues would be detrimental to the learning process, if not make learning close to impossible: the objective function would be even harder to optimize, rewards would be delayed, sparse and non-informative. Despite these open problems and limitations, we argue neural constrained text generation is an important research area which deserves a lot more attention.

Constrained text generation is useful in many scenarios, such as incorporating in-domain terminology in machine translation \[120\], improving semantic correctness \[4\], avoiding generic and meaningless responses in dialogue systems using grounding facts \[106\], paraphrase generation in monolingual text rewriting \[54\], \[63\], incorporating ground-truth text fragments (such as semantic attributes, object annotations) in image caption generation \[1\], creating a story \[25\] or poem \[39\] using a pre-defined set of keywords, or re-writing a user search query as a fluent sentence. Typical attributes used to generate constrained natural language are the tense and the length of the summaries in text summarization \[24\], the sentiment of the generated content in review generation \[107\], language complexity in text simplification or the style in text style transfer applications. In addition, constrained text generation is used to overcome limitations of neural text generation models for dialogue such as genericness and repetitiveness of responses \[131\], \[134\].

Nevertheless, generating text under specific lexical constraints is challenging. Common models and architectures employed for natural language generation are autoregressive in nature, generating tokens one by one in a sequential manner from left to right; by design, these models lack fine control over the generated sequence and cannot easily support constraints at arbitrary positions in the output or constraints.
TABLE I
OVERVIEW OF CONSTRAINED NLG TASKS, DIFFERENTIATING BETWEEN CONDITIONS AND CONSTRAINTS.

| Task                     | Condition | Lexical | Format | Semantic | Syntactic | Utility |
|--------------------------|-----------|---------|--------|----------|-----------|---------|
| Machine Translation      | source input | words phrases entities | -- | topic sentiment | paraphrase tense gender pronouns | target language politeness factuality/ faithfulness |
| Dialogue Generation      | past utterance(s) | words phrases entities | length verbosity topic sentiment toxicity | paraphrase gender pronouns | politeness personality traits factuality/ faithfulness |
| Text Summarization       | input document(s) | words phrases entities | length topic paraphrase | -- | factuality/ faithfulness |
| Text Simplification      | input text | words phrases entities | length topic paraphrase | -- | simpler vocabulary readability factuality/ faithfulness |
| Text Style Transfer      | source text | words phrases entities | length topic paraphrase tense gender pronouns | -- | style factuality/ faithfulness |
| Question Answering       | input question | words phrases entities | length topic paraphrase tense gender pronouns | -- | factuality/ faithfulness politeness |
| Narrative Generation/ Story telling | -- | words phrases entities | length topic paraphrase tense gender pronouns | -- | readability factuality/ faithfulness style |
| Poetry Generation        | -- | words phrases entities | length rhyme rhythm topic sentiment paraphrase tense gender pronouns | -- | readability factuality/ faithfulness style |

III. NLG CONSTRAINTS

Natural language generation models place restrictions on the generated output to produce texts that reflect certain user preferences. In Table I we present NLG tasks distinguishing between conditions and constraints. We broadly group existing constraints into the following categories:

a) Lexical constraints: Lexical constraints serve with the inclusion of specific keywords, phrases or entities at arbitrary positions in the output, and can be specified as a word (a single token) or phrasal constraint (a multi-word phrase). They are useful in tasks such as dialogue generation, machine translation, story telling or poetry generation.

b) Format constraints: Format constraints such as number of sentences, length of sentences, order of words, number of syllables, etc. serve to denote preferences on the form and appearance of the generated output. Format constraints are particularly useful in tasks such as poetry generation to specify the form of the generated poem, for eg. quatrain or regulated verse, length of the poem, rhyme and rhythm. In text summarization or text simplification, length constraints define the length of the generated output to be strictly less than the length of the input document, while in dialogue generation they help define the level of verbosity of the dialogue agent.

c) Semantic constraints: Semantic constraints are used to define the topic and sentiment of the generated content, or control fine-grained aspects such as removing toxicity. Topic constraints are particularly useful in dialogue generation, where the goal is to generate on-topic responses that are safe, non-harmful, unbiased, relevant to the dialogue context and particular user needs; in story telling or poetry generation, topic constraints help define the theme. Generating language that conveys particular positive, neutral or negative sentiment is important in many tasks such as dialogue generation, review generation, story telling, poetry generation or text style transfer. Furthermore, increasing politeness of a dialogue system or reducing toxicity of generated language are important aspects with respect to human-centered metrics of conversation quality.

d) Syntactic constraints: Syntactically constrained text generation produces sentences with desired syntax by incorporating syntactic templates and rules in the training of the text generative model. Syntactic constraints are useful in paraphrase generation, where given a sentence and a target syntactic form (e.g., a constituency parse), a system must produce a paraphrase of the sentence whose syntax conforms to the target. Generating texts that convey the same...
meaning but with different expressions has numerous applications in many natural language generation tasks, including monolingual transduction tasks such as text simplification, text compression, or text style transfer, as well as in tasks like text summarization, machine translation or question answering where alternative ways of expressing the same information help capture the inherent language variations.

e) Utility constraints: Utility constraints capture holistic properties of the generated output, for eg., stylistic, readability, faithfulness and politeness aspects. Preserving the information content of texts while manipulating attributes such as style, readability level, personality traits of the user or specific gender pronouns allows to customize generated texts to different audiences and make them relevant in a wide variety of end-user applications. Stylistic constraints are immediately relevant to the task of text style transfer, which has direct applicability in numerous other tasks, including dialogue generation, machine translation, text summarization, story telling, poetry generation, review generation.

Constraining text generation on attributes such as readability and level of text complexity serves to adapt the generated output to users of different age, backgrounds and educational levels. Reducing complexity of texts while preserving the information content is the main goal of text simplification; in addition, in tasks such as dialogue generation, text summarization, story telling, poetry generation, question answering it is important to customize texts for various literacy levels.

In many languages the degree of politeness is an important aspect of inter-personal communication, and honorifics are used to express courtesy, social distance, or the relative social status between the speaker and their addressee(s) [133]. Politeness constraints on the output are used in machine translation, dialogue generation, story telling, and text style transfer.

Faithfulness constraints enforce similarity between a generated text sequence and its corresponding input, requiring models to generate texts that are faithful, factual and preserve the original information content. Such constraints are important in many tasks, including text summarization, machine translation, text simplification or dialogue generation, where models are vulnerable to producing hallucinated content.

Finally, language constraints are useful when translating texts between different languages such as in machine translation, or from complex language into simple language such as in text simplification.

IV. CONSTRAINED NATURAL LANGUAGE TASKS

In what follows we briefly describe natural language generation tasks, differentiating between conditions and constraints.

a) Machine Translation: Machine translation is focusing on the automatic translation of textual content from one language into another language, and is a typical example of both conditional and constrained text generation, as it conditions on the input text in the source language and constraints the model to generate fluent and faithful output in the target language. Additional constraints can be placed on the degree of formality and politeness, the use of gender-specific pronouns, the inclusion in the target sentence of named entities or specific concepts from the source sentence.

b) Dialogue Systems: A dialogue system, also known as a conversational agent, is a computer system designed to converse with humans using natural language. Dialogue generation is an instance of conditional text generation where the system response is conditioned on the previous user utterance and frequently on the overall conversational context. Dialogue generation can also be an instance of constrained text generation - it is desirable generated dialogues incorporate explicit personality traits [172], control the sentiment [71], topic, degree of formality and politeness of the generated response to resemble human-to-human conversations. In addition, dialogue responses may need to incorporate text excerpts from past dialogue history or entities such as locations, persons, institutions, etc. From an application point of view, dialogue systems can be categorized into: i) task-oriented dialogue agents, designed to help users complete a particular task, or ii) non-task oriented dialogue agents (chat-bots) designed to carry entertaining conversations with their users on a wide range of open domains. A common problem in dialogue generation systems is that they tend to generate safe, universally relevant responses that carry little meaning [134], [81], [106]. Moreover, they can fail to take turns asking questions and balance specificity with genericness of the output [133].

c) Text Summarization: Text summarization facilitates a quick grasp of the essence of a document and produces a condensed version of its content, by copy-pasting the relevant portions from the input as in extractive summarization [108], or by generating novel content as in abstractive summarization [126], [109], [130], or via hybrid approaches [91] that combine both techniques. Text summarization is a conditional text generation task where the condition is represented by the given document(s); additional conditions are used in remainder summarization to flexibly define which parts of the document(s) are of interest, for eg., remaining paragraphs the user has not read yet, or in source-specific summarization to condition summaries on the specific input source and style of writing, for eg., newspapers, books or news articles. Text summarization is also a constrained text generation task considering that the length of the summary is fixed, pre-determined, and strictly less than the original document; this allows to digest information at different levels of granularity and detail according to user needs and time budgets. Moreover, constraints can be placed on specific concepts to include in the summary, such as named entities, or on explicitly picking sentences from the original document as in extractive summarization.

d) Text Simplification: Text simplification is designed to reduce the text complexity, while preserving its original meaning. In the literature, simplification has been addressed at multiple levels: i) lexical simplification focused on replacing complex words or phrases with simpler alternatives; ii) syntactic simplification alters the syntactic structure of the sentence; iii) semantic simplification paraphrases portions of the text into simpler and clearer variants. End-to-end models attempt to combine all these steps. Text simplification is both conditional and constrained text generation; we are conditioning on the input complex text to generate a simpler version, accounting for constraints such as higher readability, simpler vocabulary, and shorter sentence length than the complex input.
e) **Text Style Transfer**: Style transfer has its origins in computer vision applications for image-to-image translation and more recently has been used in natural language processing applications for machine translation, sentiment modification to change the sentiment of a sentence from positive to negative and vice versa, word substitution decipherment and word order recovery [53]. Text style transfer is designed to preserve the information content of a source sentence while altering the way it is delivered to meet desired presentation constraints. Textual content is disentangled from the style in which it is presented, and manipulating stylistic attributes can be done without parallel aligned data between source and target styles. Text style transfer is an instance of both **conditional and constrained text generation** given that we condition on the given source text and constrain the transferred sentences to stylistically match target examples.

f) **Question Answering**: Question answering systems are designed to find and integrate information from various sources to provide responses to user questions [31]. While traditionally candidate answers consist of words, phrases or sentence snippets retrieved and ranked appropriately from knowledge bases and textual documents [72], answer generation aims to produce more natural answers by using neural models to generate the answer sentence. Question answering is both **conditional and constrained text generation** task; the system conditions on the user question, and simultaneously ensures that concepts needed to answer the question are present in the generated output. Diverse question answering systems are proposed in the literature addressing for eg., medical information needs [156], mathematical questions [129], quiz bowl questions [57], cross-lingual and multi-lingual questions [94]. Notably, in practical applications users are not only interested in learning the exact answer word or phrase, but also in how it relates to background information and to previously asked questions and answers [31].

g) **Narrative Generation / Story Telling**: Neural narrative generation is an important step towards computational creativity [37] and represents a long-form open-ended text generation task which simultaneously addresses the selection of appropriate content ("what to say") and the surface realization of the generation ("how to say it") [137]. Narrative generation is a **constrained text generation** task that places explicit constraints on concepts to steer the narrative in particular topic directions and expands the few keywords specified as the story title. While existing models can generate stories with good local coherence, generating long stories is challenging. Difficulties in coalescing individual phrases into coherent plots and in maintaining character consistency throughout the story lead to a rapid decrease in coherence as the output length increases [145]. Hierarchical models for story generation break down the generation process into multiple steps: first modelling the action sequence, then the story narrative, and finally entities such as story characters [26]. Neural narrative generation combining story-writing with human collaboration in an interactive way improves both story quality and human engagement [45].

h) **Poetry Generation**: The poem generator operates in an interactive context where the user supplies the model with a set of ordered concepts that reflect her writing intent, as well as the format of the poem, for eg. quatrain or regulated verse. Poetry generation is a **constrained text generation** problem since user defined concepts need to be included in the generated poem, and a **conditional text generation** problem given the explicit conditioning on stylistic attributes. For a detailed overview of poetry generation please see [114].

V. **Constrained NLG Methods**

Accounting for the different types of constraints introduced in Section III we distinguish five methodologies commonly employed in the constrained text generation literature: i) decoding approaches, ii) fine-tuning approaches, iii) discriminative approaches, iv) edit-based approaches, and v) adapting existing models and architectures to accommodate constraints on the generated output. In what follows we present each approach in detail, outlining the main associated challenges.

A. **Decoding approaches**

   a) **Lexical constraints**: **Lexically constrained (guided) decoding** aims to restrict the search space at decoding time to sequences which contain pre-defined lexical constraints only. These lexical constraints can be specified in the form of a word constraint (a single token) or a phrasal constraint (a multi-word phrase, i.e. a sequence of two or more contiguous tokens). To this end, the beam search decoding algorithm is modified to enforce the inclusion of pre-specified words and phrases in the generated output by allowing the model distribution to not only account for the given lexical constraints, but also to generate parts of the output sequence not covered by the constraints. In general, the decoder can more easily place multiple sequential tokens in a phrasal constraint (where the permutation order is fixed) on the generated output as opposed to placing multiple separate, independent constraints. In addition, the lexically constrained decoding approach assumes lexical constraints are pre-determined, which may not always be the case; if so, the open question is where to get lexical constraints from.

Early work on constrained decoding in machine translation relies on the **placeholder approach** designed to recognize identifiable elements (numbers and named entities) in the source sentence, temporarily replace these with corresponding placeholders during preprocessing, and then substitute the assigned placeholders with the original source-language strings during beam search decoding [21]. Nevertheless, such an approach is limited and unable to model the source tokens in target language specific terminology or the vocabulary from a new out-of-distribution domain. **Prefix decoding** represents a modification of beam search to first ensure that a user defined target prefix is generated first, and only after build hypotheses for the suffix that maximize the coverage of the remaining source-side tokens. As decoding progresses from left to right, the decoder transitions from a constrained prefix decoding mode to unconstrained beam search. For example, the start of the sentence symbol \(<s>\) can be easily included as the first word of a constraint [70], [159]. In the context of text summarization, an essential property of a summarization system is the ability to generate a summary with desired
length. **Grid beam search** \[50\] extends beam search decoding to allow for the inclusion of arbitrary target side hard lexical constraints at any position in the generated sequence. Given $C$ input constraints, the algorithm maintains $C + 1$ separate beams $B_0, B_1, \ldots, B_c$ that group together hypotheses which meet the same number of satisfied constraints. Decoding runs similar to beam search, with an additional dimension added to keep track of how many constraints are met by each hypothesis at every timestep; the highest scoring hypothesis in beam $B_c$ is ultimately generated. However, grid beam search is impractical as decoding complexity is linear in the number of constraints, i.e. beam size increases proportionally to the amount of constraints and changes for every sentence.

**Constrained beam search** \[1\] guarantees the inclusion of input constraints in the generated sentences by extending beam search with a finite state machine whose states mark completed subsets of the input set of constraints; however, decoding complexity has an exponential cost in the number of constraints, making it infeasible in many applications.

**Dynamic beam allocation** \[120\] improves upon the runtime complexity of grid beam search and constrained beam search by decoding with constant complexity $O(1)$ in the number of constraints. The algorithm still groups together hypotheses that have met the same number of constraints by using a single fixed-size beam which is dynamically divided at each time-step according to how many constraints have been met. Despite being more efficient, dynamic beam allocation does not necessarily outperform conventional beam search \[86\]. In addition, the generation of hypotheses that only partially satisfy a phrasal constraint needs to be aborted to unwind the tokens in the constraint. **Neurologic decoding** \[65\] modifies beam search to enforce the satisfaction of lexical constraints expressed under predicate logic in conjunctive normal form (CNF). Given the intractability of exhaustive beam search to optimize CNF constraints, the algorithm searches for approximately-optimal output sequences in which all clauses are satisfied, including both positive and negative constraints (i.e. words that must be generated, respectively omitted in the output sequence). The method is applied to cooking recipe generation, where the task is to generate cooking instructions given a dish name and a list of ingredients, and to data-grounded dialogue response generation where a response is generated given a query and a list of facts to convey.

In general, lexically constrained decoding methods have high computational complexity and force the inclusion of specific words in the generated sentence at every timestep of the generation process with no prior examination of these specific words before generation begins \[78\]. This unnatural way of generating sentences can impact the quality and naturalness of the generated output \[90, 120\]. In lack of suitable evaluation metrics, there is no commonly agreed criteria for objectively assessing the quality of the generated sentences and conducting comparisons across text generation models.

**b) Format constraints:** **Fixed length decoding** \[67\] constrains the length of generated summaries in two ways: i) by preventing the decoder from generating the end-of-sentence tag until the length of the generated sequence exceeds the desired length, and ii) by defining the minimum and maximum length range of the sequence and discarding out-of-range sequences. **Non-monotonic decoding** approaches allow tokens to be inserted at any position in the generated sequence during decoding, therefore accommodating flexible orderings of the output. Unlike left-to-right autoregressive generation that produces a single word at a time, non-monotonic decoding can satisfy lexical constraints at multiple locations in the output sequence allowing for highly parallel generation and faster decoding times. Nevertheless, such approaches assume the generated sequence length is known a priori, preventing it from being dynamically adjusted as generation proceeds. Moreover, such models assume conditional independence between output tokens, i.e. tokens are generated independently, and may be inconsistent and agnostic to each other. Consequently, this approach may hurt the expressiveness of the model and lead to potential performance degradation, impacting the fluency and naturalness of the generated output. In addition, non-monotonic sequence decoding approaches can terminate prematurely before constraints are satisfied in the output sequence \[168, 53\]. The main limitation of this approach is the lack of model expressiveness in accommodating constraints.

**Insertion Transformer** \[146\] proposes a flexible sequence generation framework based on repeated insertion operations into an initially empty output sequence until a termination condition is met. The model adopts a progressive masking approach based on token importance in the original text and is trained to generate a missing token between every two tokens in the input. To this end, the original Transformer \[150\] decoder is modified to allow insertions not just at the end but anywhere in the output sequence. The model can decode sequences serially one token at a time, or it can decode sequences in parallel with simultaneous insertions at multiple locations. A similar approach is considered in InDIGO \[45\] which extends Transformer for insertion-based decoding with inferred generation order. Token generation order for the output sequence is modeled as a latent variable, and at each decoding step the model predicts both the generated word and its position in the output sequence; nevertheless, strong conditional independence is assumed between the output tokens which hurts output quality. An iterative refinement step based on latent variables is added to the Transformer decoder to refine a target sequence gradually over multiple steps until a predefined stopping criterion is met \[80\]. **Progressive Insertion Transformer** \[168\] uses non-autoregressive modeling based on a top-down progressive structure for lexical hard-constrained text generation. Given lexical constraints as input, the model inserts tokens progressively according to word importance to generate the target sequence, as follows: first it generates high-level words in a sentence such as nouns, adjectives and verbs, then uses these as pivoting points to insert details of finer granularity and finally completes the sentence by adding connecting words which carry less information, such as pronouns and prepositions. **Entity Constrained Insertion Transformer** \[53\] builds upon previous models considering hard lexical constraints in the form of entities in the output sequence. Similar approaches train the Transformer decoder to insert missing tokens in a partially complete sequence without relying on a pre-specified factorization of tokens \[15\].
Human preference learning is considered crucial for safely deploying artificial systems in real-world tasks. The reward model is derived from human preferences on text continuations with positive sentiment or vividly descriptive language. Importantly, a KL constraint is used to prevent the fine-tuned model from drifting too far from the pre-trained model and encourage the new policy to remain close to the prior policy. Similar KL control has been used in dialogue systems to retain prior information and penalize divergence from the pre-trained model during RL fine-tuning [59]. Controlled text generation from pre-trained language models is formalized as a constraint satisfaction problem, where pointwise constraints focus on the quality of each individual output while distributional constraints enforce collective statistical properties desirable over the set of all generations [66]. Similar to prior work, a KL penalty term is used to discourage large deviations from the pre-trained language model as a proxy for sample quality. The lack of suitable evaluation metrics is an outstanding challenge in generating high quality outputs.

Pre-trained OpenAI-GPT2 [123] model is used to re-write a story through counterfactual reasoning and generate a narrative consistent with the imposed constraints [121]. In abstractive summarization, OpenAI-GPT2 is used in a reinforcement learning setting which trains the summarization agent to maximize coverage and fluency of the generated content constrained on a pre-defined length [76]. RecipeGPT [48] fine-tunes the GPT-2 pre-trained language model for generating cooking instructions when hard constraints are placed on the recipe title and ingredients; the model can also generate the list of ingredients for a recipe when constrained on the recipe title and specific cooking instructions.

While fine-tuning models on task specific datasets has become the dominant paradigm for constrained text generation from large pre-trained language models, these models generally fail to reliably incorporate the underlying constraints in the generated texts even when supervised with large amounts of task-specific examples [65]. Notably, fine-grained constrained text generation is limited even with large scale pre-trained neural networks. The main challenges are the lack of model expressiveness to incorporate constraints and the lack of constrained text generation datasets for fine-tuning these models.

C. Discriminative approaches

a) Utility constraints: One of the early works to propose constrained generation and manipulation of the generated text learns disentangled latent representations by combining variational auto-encoders with attribute discriminators [55]. Semantic structure is imposed on the latent codes by using global discriminators, one for each attribute, to guide the learning of the discrete text generator and force it to allocate one latent dimension per attribute code. The model is used to generate sentences with constrained sentiment and tense.

Weighted decoding [51] relies on a mixture of discriminative models to guide a recurrent generator towards incorporating attributes that enhance the overall coherence, style, and information content of the generated text. The discriminators complement each other and their weighted contributions form...
the final decoding objective from the generator. Similarly, stylistic configurations are revised and polished for generated poems by adding additional weights during decoding to control the style of generated poem, including the repetition, alliteration, word length, cursing, sentiment, and concreteness [39]. Nevertheless, modifying the scoring function used for generation as in weighted decoding often leads to sacrificing fluency and coherence of the generated text [131]. Selective sampling [153] relies on a sample selector (multilayer perceptron for binary classification) which outputs whether the current sample should be accepted or rejected based on the presence of desired target words that define the output style and topic in the generated sequence. The robustness of evaluation metrics is directly correlated with model performance, therefore it is crucial to focus on developing metrics that capture diverse aspects of text quality during training and sampling time.

Generating texts with desirable attributes from a pre-trained unconditional language model \( P(X) \) is a non-trivial task. Most approaches resort to either training from scratch a new conditional model \( P(X|a) \) for desired attribute \( a \), or fine-tuning \( P(X) \) on additional data representative for the attribute \( a \). Theoretically, rejection sampling could also be used to sample \( P(X|a) \) from \( P(X) \), but this approach is highly inefficient in practice. Fudge [161] generates text conditioned on a desired attribute \( a \) (for eg., topic control in language generation, degree of formality in machine translation, poetry couplet completion) while only accessing the output probabilities \( P(X) \) of generative model \( G \). Given an incomplete sequence prefix, the model trains binary discriminative models for one or multiple desired attributes to predict whether the attribute(s) will be fulfilled in the future complete sequence, therefore evaluation is an important challenge. The output probabilities of the discriminator(s) are then multiplied with the output logits of the generator \( G \) to adjust the original probabilities of \( G \) accounting for desired attribute(s) \( a \) and model \( P(X|a) \) via a Bayesian decomposition.

PPLM [22] combines a pre-trained language model with attribute classifiers that guide generation towards specific topics and sentiment styles. These classifiers are trained on top of the last hidden layer of the pre-trained language model, and gradients from the classifiers are backpropagated to update the hidden representations of the language model and steer generation in desirable directions. While PPLM achieves fine-grained control of content and style attributes via a simple gradient-based sampling mechanism, the approach is computationally intensive and inefficient as it requires multiple forward and backward passes for each generation step. Plug-and-play methods have been used to control large pre-trained conversational models such as GPT-2 [123] using a variety of styles (positive and negative sentiment) and topics (Question, Sport, Business, Finance) [99]. Undoubtedly, more effort needs to be focused on collecting datasets for constrained text generation that capture many possible real-world constraints.

GeDi [73] guides language generation from large language models towards desired attributes by using generative discriminators to compute classification likelihoods for all candidate next tokens on the fly at generation time. Given a class-conditional language model conditioned both on a desired attribute \( c^+ \) and an undesired attribute \( c^- \), GeDi-guided contrastive generation uses the two instances of the model as discriminative classifiers to contrast and filter out common attributes between the two classes \( c^+ \) and \( c^- \); then aspects of the desired attribute \( c^+ \) are transferred across domains via weighted decoding and filtering. The contrast between a positive and a negative class conditional distribution is employed both at training and inference time to control the bias, toxicity and negativity of GPT-2 [123] and GPT-3 [11].

D. Edit based approaches

a) Utility constraints: Edit based approaches rely on the key idea that changing only a few words or phrases which are indicative of a particular attribute are sufficient to alter the style of a given piece of text. For example, the sentiment of a sentence can be altered from negative to positive by first identifying negative attribute markers ("bad", "worst", "disappointed"), deleting these negative attributes while keeping other content words fixed, and then generating the final output via a recurrent decoder which conditions on the extracted content words and the target attribute [65]. Leaving from the observation that humans write text in incremental passes with multiple revisions, a prototype-then-edit model first samples a prototype sentence from the training corpus and then edits it conditioned on an edit vector [47]. Noticeably, text generation based on editing a prototype is much easier compared to generating text from scratch. Also building upon the "Delete Retrieve Generate" framework, the Generative Style Transformer [147] incorporates a neural mechanism to delete style attributes from the source sentence based on the attention weights of a Transformer model (Delete Transformer), and then generates sentences in the desired target style by decoding with a pre-trained GPT-2 [122] model.

b) Lexical constraints: Constrained sentence generation by Metropolis-Hastings sampling [103] first inserts all constraint keywords in a template in random order, then samples local edit operations (word replacement, deletion or insertion) to perform at specific positions for improving sentence fluency. The probability of each edit operation being accepted or rejected is determined by a language model, however individually sampling each token results in slow convergence. Instead of randomly sampling edit operations, the gradient of a differentiable objective function is used to determine where and how to edit [137].

E. Adapting existing models and architectures to accommodate constraints

It is non-trivial to impose constraints on existing deep learning models while maintaining high generation quality since their model architecture is designed to generate sentences sequentially from left to right. While current deep learning models are lacking the expressiveness to incorporate constraints at training time and at arbitrary positions in the generated sequence, well known models and architectures are adapted to accommodate constraints through a set of custom engineered approaches. We present these methods below.
Specific directions is achieved by:

1) Adding special tokens at the beginning or end of the source text.
2) Incorporating additional conditions into the decoder hidden states and iii) connecting the conditions directly to the decoder output layer. A topic aware sequence-to-sequence model is used to generate on-topic conversational responses by conditioning the decoder on specific topic words [160]. Imposing conversational goals on dialogue agents aims to guide the conversation towards a designated target subject by combining coarse-grained topic constraints with discourse-level rules [148]. Generating emotional responses in neural conversational systems is achieved by feeding the emotion category embedding to a sequence-to-sequence decoder [174].

For integrating factual knowledge into open-ended conversational systems, factoid and entity-rich web documents are encoded altogether with the conversation history into the same representation which is passed to an attentional neural decoder that generates the response tokens. Similarly, speaker-level representations are integrated into seq2seq convolutional models for generating personalized conversation responses [82]. Fact-guided sentence modification for dynamically rewriting, updating or correcting articles according to changing information is an instance of constrained text generation which presents the particular challenge that the rewritten sentence needs to be consistent with an input claim while at the same time preserve non-contradicting content [138]. Given the claim and an old sentence, an updated sentence is produced by first identifying contradictory components in the input sentence, masking these, then using the residual sentence and the claim as input into a two encoder sequence-to-sequence model with copy attention to produce the update sentence consistent with the claim. Syntactically controlled paraphrase generation produces paraphrases of an input sentence by constraining the system on the target syntactic form [48], however not many syntactically constrained datasets to learn from are available.

Controllable story generation based on RNNs is used to influence the story ending valence (whether happy or sad) and the storyline (specified as a sequence of words) [118]. Story-telling methods commonly use a hierarchical approach to thematically consistent story generation, by first generating a prompt describing the topic for the story, and then constraining on the prompt for generating the story content [28]; additionally, constraints on the presence of entities are included as well [20]. Open-domain story generation requires composing coherent natural language texts that describe plausible sequence of events and is more challenging compared to generating stories in a narrow domain given an existing plot.

Unsupervised machine translation methods are adapted for the task of text-style transfer by incorporating stylistic constraints in a neural seq2seq model with attention and using a style classifier to guarantee the accuracy of style transfer [169], or for control over multiple style attributes, including gender, sentiment or product type [77]. In machine
translation, honorifics constraints are important for producing socially appropriate forms of address and controlling the level of courtesy [133]; the system user defines the desired level of politeness of the translation, however these user-defined constraints are only soft constraints and can be overridden by the attentional encoder-decoder machine translation system whenever the source text provides strong politeness clues.

For effective imposition of semantic structure in constrained text generation, latent space representations need to be disentangled [62], such that varying an individual latent code will only change a single desired attribute. VAEs can achieve meaningful latent representations with designated semantics when combined with attribute discriminators and optimized end-to-end with differentiable softmax approximation [55]; this allows to generate sentences with constraints on sentiment and tense. Given an input sequence and a set of labels, sequence transduction with multi-space variational autoencoders [173] generates an output sequence that alters the content of the input sequence according to the constraints specified by the labels; the method is used for morphological inflection in multiple languages. In general, constrained text generation approaches assume that constraints need to be known a priori; however, this is not always possible, for eg., when suggesting alternative phrases for search queries in real-time, or when generating responses in dialogue systems according to the dynamics of the conversational context. Recent constrained text generation approaches control attributes of a generated sequence based on another sentence example: given two sentences X and Y, the goal is to generate a new sentence Z that follows the semantics of X and the syntax of Y. To this end, a VAE model with two latent variables is used to achieve disentanglement in the continuous latent space between syntax and semantics [16], [6]. Topic guided VAEs [154] use a Gaussian mixture model prior where each mixture component corresponds to a latent topic extracted from data as opposed to using pre-defined parameter settings which do not incorporate semantic meaning into the latent codes; the model is used for text summarization with designated topic guidance. Abstractive and extractive sentence compression with VAEs assumes the existence of a background language model from which a latent summary sentence is drawn first, and then the observed sentence is generated conditioned on the latent summary [104]; the model is able to balance copying a word from the source sentence with generating it from the background distribution. Iterative refinement of a sequence to transform it into another sequence with desired attributes exploits geometry of the latent space to produce incremental higher-quality revisions with theoretical guarantees in the combinatorial space of sequence elements [107], [139]. Such latent variable manipulations allow to rewrite modern text in the language of Shakespeare, improve sentence positivity, address word substitution and word order recovery tasks without need for any revision examples. Constraints on the use of metaphor and personification in poems are incorporated in a conditional VAE with a rhetorically controlled decoder trained to emit meaningful and diverse rhetoric and overcome generic sentences [92]. Variational neural machine translation [163] incorporates a continuous latent variable to model the underlying semantics of sentence pairs. Nevertheless, efficiently performing posterior inference and large-scale training during the incorporation of latent variables remains an open challenge for constrained VAEs.

Modifying textual attributes of sentences including sentiment, style, tense, voice, mood and negation is achieved by incorporating conditioning information into a neural encoder-decoder model, and optimizing a reconstruction loss which interpolates between auto-encoding and back-translation components to encourage content compatibility, as well as an adversarial loss which encourages sentence-level stylistic attribute compatibility [93]. The model allows simultaneous conditioning on multiple textual attributes, however the extent to which the generated sentences match the conditioning information requires new objective evaluation metrics for attribute accuracy and content compatibility/preservation. Style transfer between scientific papers and newspapers is performed with separate style decoders, or by generating both content and style from the same decoder [52].

In poetry generation, it is common to impose hard constraints on rhyme, rhythm, and topic [58], [39]. Given a user-supplied topic, the poetry generation algorithm first generates a large set of on-topic words and phrases, assigns rhyming words and phrases to specific lines, and then combines finite-state machinery with an RNN language model to score plausible poems that meet the desired constraints. While augmenting an RNN with a working memory to explicitly maintain a limited history of generated topics and context, coherence in meaning and topics across the overall poem remains an important challenge [160].

Constrained recurrent models are also used to generate online product reviews of certain topic, sentiment, style and length [28], affective dialogue responses [40], or for modeling participant roles and topics in conversational systems [102].

b) Format and Utility constraints: Text simplification models parameterized on constraints such as length, amount of paraphrasing, degree of lexical and syntactic complexity are used for generating texts easier to read and understand with simpler grammar and structure [100]. Towards a similar goal of controlling the degree of lexical complexity, the training loss function is changed to assign weights to words based on their complexity level [112]. In text summarization, constraints on the output sequence length for neural encoder-decoder models are specified as length embeddings and are passed as additional input to the decoder [67].

Faithfulness in abstractive text summarization is enforced in a seq2seq model by conditioning on both the source text and extracted factual descriptions [13]; this helps avoid generating false facts in the output summary. Hybrid text summarization approaches combine an unsupervised sentence extractor which selects salient sentences from the input document with a sentence abstractor that paraphrases each extracted sentence to overcome limitations of parallel aligned datasets [111].

Reinforcement learning is used in the context of constrained natural language generation to directly optimize non-differentiable reward functions and evaluation metrics. While any user-defined reward function can be employed for training, most frequently optimized metrics with RL are BLEU for machine translation [124], ROUGE for text summarization [124].
constrained optimization with RL often leads to sparse, non-informative and delayed reward signals. Neural reward once it reaches the end of a sequence and updates its internal state consequently. To this end, policy gradient methods are used to train text generative models and alleviate issues such as exposure bias and loss functions which do not operate at the sequence level. However, policy gradient algorithms present large variance and generally struggle in settings with large action spaces such as natural language generation. In addition, they take very long time to converge and the improvement in the optimized metrics is not always reflected in human evaluations of text quality. Training RL models to optimize n-gram evaluation measures based on local patterns provides only a limited and myopic perspective of overall text quality and does not necessarily lead to better text quality, overall coherence or discourse structure [9]. Moreover, fine-tuning on such measures may yield deteriorated outputs despite increased automatic scores, while difficulty in constrained optimization with RL often leads to sparse, non-informative and delayed reward signals.

Learning RL rewards from human preferences aims to incorporate human feedback in text generation. Neural reward learning schemes train neural teachers that learn to score an ordered sequence of sentences and formulate rewards that guide coherent long text generation [9]; the approach is used for generating cooking recipes given the dish title and the set of ingredients as constraints. Learning-to-rank algorithms are used to approximate ground-truth oracle rewards in extractive multi-document summarization to indicate the quality of a summary or preferences over summary pairs [35]. Machine learnability of human rewards in neural machine translation models is approached by first training reward estimators on rewards collected from offline logs, then integrating these reward estimators in an off-policy RL setting [74]. Similarly, implicit human reactions such as sentiment or length of a conversation are used to learn rewards for fine-tuning off-policy RL models for dialog [59]. Nevertheless, human feedback is noisy, not well-defined, complex and inconsistent. Using RL to improve system outputs with respect to human-centered metrics of conversation quality is highly dependent on developing robust metrics tailored to the particular application domain, for eg. increasing politeness of a technical-support system or reducing toxicity of generated language.

Hard-constrained text generation in a non-monotonic order relies on a tree-based text generation scheme, where a word is generated at an arbitrary position in the sentence, then binary trees of words to its left and right are recursively generated [155]. Learning proceeds in an incremental fashion in an imitation learning framework, where the policy gradually moves from imitating the oracle to reinforcing its own preferences and generating texts without a pre-specified word order. Nevertheless, the time complexity of the approach is $O(n)$, same as for autoregressive models and the constructed tree does not reflect a high-level to low-level hierarchy of concepts.

VI. CONSTRAINED NLG EVALUATION

Evaluation of constrained text generation is performed using the same evaluation approaches and methodologies available in the natural language generation literature. In general, evaluation of the generated text is largely an unsolved and notoriously difficult problem [8]. Currently, there is no well-established consensus on how NLG systems should be evaluated. [79], [42], and the lack of meaningful quantitative evaluation metrics to accurately assess the quality of trained models is detrimental to the progress of the field. In the absence of well established evaluation measures, natural language evaluations are carried in a rather ad-hoc manner with a lot of variability across the proposed models and tasks on inconsistent benchmarks, resulting in misleading performance measures. Subjective evaluations based on visual inspection of the generated samples are often lack scientific rigour and make it difficult to quantify and judge precisely the quality of a generative model [49]. In what follows we review the main methods for constrained text generation evaluation.

a) Lexical constraints: Measuring how many of the given lexical constraints are included in the generated outputs is done using concept coverage [86], [95]: the metric is computed as the the average percentage of input concepts that are present in the lemmatized outputs.

b) Semantic and syntactic constraints: Surface similarity based on n-gram overlap metrics, such as BLEU [115], ROUGE [87], METEOR [5] measure to what extent the generative model can preserve content by retaining words commonly shared between the generated output and ground-truth references. Such metrics are commonly used to measure response relevance in dialogue systems [33], [82], translation quality in neural machine translation [133], assess summary quality in text summarization [130]. In general, the correlation between word overlap metrics and true text quality is a widely debated topic [84]. Evaluation metrics based on local n-gram patterns only provide a limited and myopic perspective of overall text quality and are notoriously poor at evaluating dialogue systems [89], [131], [9].

Perplexity [60] based evaluation metrics are used to evaluate and compare language models, and measure the fluency and diversity of the generated samples [99], [9]. Reverse Perplexity [170] and Forward Perplexity [68] scores are calculated by training language models on synthetic samples, respectively real samples, and then using these trained models to measure perplexity real samples, respectively generated
samples. Nevertheless, perplexity is a model dependent metric, and “how likely a sentence is generated by a given model” is not directly comparable across different models. Moreover, numerous studies find perplexity to be an inaccurate measure of text quality [149], [27], since models with high likelihood can generate low-quality samples, while samples of good quality can present low likelihood. In addition, infinite perplexity can still be obtained from a perfect model even when its ability to generate test sentences is removed [49].

P, R, F1 are used to measure the distance of the generated samples to the real data manifold [96]. When precision is high, the generated samples are close to the data manifold, and when recall is high, the generator outputs samples that cover the manifold well. Metrics that aggregate precision and recall such as $F_β$, a generalization of the $F_1$ score, are used to quantify the relative importance of precision and recall [127]. Nevertheless, the data manifold of non-synthetic data is unknown and therefore impossible to compute in practice.

**Content diversity** measures how different the generated sentences are from each other, by either considering word choice, topic and meaning [151], [41], [56], or by looking at the level of sentence interestingness or unlikeliness [49]. Perplexity on a reference set, $n$-gram diversity [81] and Self-BLEU [179] are commonly used measures of the diversity of the generated samples. In addition, Backward-BLEU [142] evaluates test data using the generated samples as reference; the higher the score the more diverse the generator output. Lexical diversity [2] calculates the ratio of unique tokens to the total number of generated tokens. Similarly, Distinct-$k$ or Dist-$k$ [81] measures the total number of unique $k$-grams normalized by the total number of generated $k$-gram tokens to avoid favoring long sentences. Nevertheless, the Dist-$k$ metric ignores the fact that infrequent $k$-grams contribute more to diversity than frequent ones and assign same weight to all $k$-grams that appear at least once. Distinct-1 and Distinct-2 are used to measure the diversity of constrained conversational responses [3], [167] and rhetoric constrained generated poems [92]. Entropy based metrics such as Ent-$k$ [167] reflect the frequency difference of $k$-grams and to analyze the information content of the generated responses in dialogue systems [135], [106].

Unlike traditional evaluation metrics based on heuristics, learnable metrics train machine learning models on human annotated datasets to learn a scoring function that reproduces human judgements. **Fully-learned metrics** leverage existing datasets of human ratings to learn automated evaluation metrics that fit the human data distribution, and can be tuned to measure specific properties of the generated texts, such as fluency, style, grammaticality, fidelity, etc. Linear regression based on human judgements is used to learn a model for scoring system summaries [119]. RUSE [143] combines sentence embeddings in a multi-layer perceptron regressor model. ESIM [17], [101] feeds the encoded representations of the candidate and the reference sentence into a feedforward regressor. BLEURT [132] fine-tunes BERT [23] on human ratings datasets for similarity score prediction. MAUDE [144] is proposed for the evaluation of online dialogue conversations and leverages sentence representations from pre-trained BERT to train text encoders which can distinguish between valid dialogue responses and fake examples. BARTScore [162] formulates the evaluation of generated text as a text generation task from pre-trained language models and measures the weighted probability of the generated text given another text as input or output. **Hybrid metrics** combine learnt elements with human-defined logical rules, for example, contextual embeddings with token alignment rules. BERTScore [165] evaluates generated text against gold standard references using soft-string similarity matches (i.e. cosine similarity) computed on pre-trained contextualized BERT [23] token embeddings. MoverScore [171] combines contextualized representations of system and reference texts with semantic measures of distance computed using Word Mover’s Distance [75]; the metric is extended to evaluate multi-sentence texts [19]. Human and statistical evaluation are combined in HUSE [49], an evaluation framework which estimates the optimal error rate of predicting whether a piece of text is human-written or machine-generated. However, a limitation of learned evaluation metrics is that they generally fail to generalize well across different systems [14].

**Utility constraints** A commonly used approach in the literature to assess whether generated texts have desirable attributes is to rely on an attribute classifier and measure the **classification score**, i.e. the fraction of outputs generated by the model having the desired attribute [55], [139], [85]. **Adversarial evaluation** [10], [64] employs an evaluator trained to distinguish machine-generated from human-written texts, analogous to the discriminator in GANs [44]. On this note, **pre-trained attribute classifiers and class-specific discriminators** measure how well the generated samples match the conditioning labels on attributes such as sentiment, tense, voice, mood and negation [93], [83], [12], and guarantee the accuracy of stylistic text transfer [169], [139]. GLEU [110] was originally proposed for grammatical error correction, and later adopted for the evaluation of text style transfer since both tasks require localized edits to the input sentence; GLEU is found to present a reasonable balance between target style match and content retention [147].

**Readability metrics** such as Flesch-Kincaid Grade Level [69] and Flesch Reading Ease [29] are used to account for simplicity and measure the reading difficulty of a piece of text. Both metrics are computed as linear combinations of the number of words per sentence and number of syllables per word with different weighting factors.

**All constraints** While automated evaluation helps assess generated texts quickly and cheaply, the use of automated evaluation metrics is dependent upon their correlation with human judgements of quality [30]. **Human evaluations** remain the gold-standard in natural language generation and automated evaluation metrics can only be used as a proxy for human judgements only when there is reasonable correlation with human decisions. Ideally, automated evaluations are carried simultaneously with human annotation studies, and not as a replacement of human evaluations. In text style transfer, human evaluations are conducted to determine how accurately constrained text generation methods identify stylistic textual attributes in the source input and replace these with desired target attributes in generated sentences [147]. In conversational systems, responses generated by open-domain chatbots are
evaluated across two dimensions: i) humanness, as a proxy for the fluency and coherence of the generated responses, and ii) attribute consistency, to determine whether the style and topic of the conversation. Outputs generated by neural conversational systems are also assessed for quality, style and topic to determine whether the acquisition of styles of famous personalities, characters, or professionals is achievable, and whether the topic of the conversation can be influenced in particular directions [153].

VII. Discussion and Open Challenges

In what follows we review the main challenges associated with constrained text generation outlining why these challenges have not been solved yet, and present the most promising research directions to focus on next.

In our view, constrained text generation is a more difficult problem compared to other instances of text generation. The difficulty arises from a multitude of factors, including lack of model expressiveness which makes it difficult for current models to incorporate constraints into the objective function, lack of suitable evaluation metrics to assess the extent to which constraints are satisfied (and this becomes even more challenging when there are multiple constraints present), difficulty in the constrained optimization of non-differentiable reward functions, and finally lack of constrained text generation datasets that are illustrative of a wide diversity of constraints. Due to these pressing unsolved issues, constrained text generation remains an open challenge in the research community. Advancing the state-of-the-art requires considerable more collective and focused effort. Below we identify the most promising directions for advancing the state-of-the-art for safe and robust constrained NLG.

Multiple constraint satisfaction Most approaches proposed for constrained text satisfaction focus on generating sentences that meet one single desired constraint, nevertheless generating sequences that simultaneously satisfy multiple lexical constraints is an important open research problem in text generative models [90], [78], [53]. While incorporating one constraint is already hard enough due to lack of model expressiveness, incorporating multiple constraints poses significant challenges in terms of defining the loss function accounting for all the desired constraints, difficulty in optimizing it and evaluating whether each constraint is satisfied. Approaches that convert the multiple constraint satisfaction problem into allowing the inclusion of pre-specified lexical constraints at decoding time are not optimal either: on the one hand, decoding complexity increases exponentially or linearly in the number of constraints, and on the other hand forcing constraints at every step of the generation process impacts the quality and naturalness of generated texts [120]. Moreover, many model architectures are designed for sequential sentence generation only (vs. non-monotonic text generation) and it is non-trivial to impose decoding time constraints while maintaining optimal text generation quality [103].

Dynamically defined constraints Current approaches to constrained text generation assume there is prior knowledge of the constrained textual attributes and the finite set of values these attributes can take on. Nevertheless, there are situations when it may be desirable to impose constraints dynamically, for eg. in conversational systems depending on the system user’s statements, reactions and emotions. When dynamically defining constraints, the main challenges are the lack of model expressiveness and robust ways to evaluate whether these constraints are satisfied. In the literature, controlling the realization of a sentence based on another’s sentence syntax and semantics is a less explored setting for constrained text generation with dynamic constraints which does not require prior knowledge of all the values the control variable might take on [16]. To this end, disentangled latent space representations of syntax and semantics are essential for the manipulation sentence attributes in tasks such as unsupervised paraphrase generation and syntax-transfer generation [3].

Generative reasoning Current large-scale text generation models display impressive ability to generate fluent texts, nevertheless composing realistically plausible sentences in the presence of constraints remains a significant open challenge. This is illustrative of all challenges associated with constrained text generation, including lack of model expressiveness, lack of suitable evaluation metrics, difficulty in constrained optimization and lack of constrained text generation datasets. Nevertheless, endowing generative models with commonsense reasoning abilities is an important milestone towards advancing machine understanding and intelligence. CommonGen [86] benchmark proposes the task of constrained text generation with generative commonsense reasoning, where given a set of concepts the task is to generate a coherent sentence describing an everyday scenario using the given concepts. To do this successfully, the generative model must reason over commonsense relations between the given concepts (relational reasoning), and infer novel combinations of familiar concepts (compositional generalization). Preliminary analysis shows that current state-of-the-art pre-trained models struggle at the task and generate implausible sentences by a large margin.

Attribute specific datasets The lack of annotated datasets for attribute specific text generation constitutes a bottleneck in the development and adaptation of models for tasks that require fine-grained control over style and topics. For example, in dialogue systems the absence of attribute annotated conversational datasets that can be used for fine-tuning large scale pre-trained models limits control over the generated responses for a desired attribute [99]. Moreover, such attribute annotated datasets can help with the personalization of dialogue systems, make dialogues safe, supportive and engaging [138], [164]. Personalized dialogue agents that display consistent personalities and viewpoints overcome the unsatisfying experience of a persona-free chit-chat model. Nevertheless, imposing conversational goals on a dialogue agent for learning target-guided strategies requires keyword-augmented conversation datasets for learning how to steer the conversation towards a designated target subject [148]. The collection of datasets that capture a wide diversity of constraints and are representative of many real world situations are critical for advancing safe
and robust constrained text generation. Existing benchmarks focused on politeness [98], formality [125], sentiment [139], writing style [61] are rather limited in nature and do not offer fine-grained control over stylistic attributes. StylePTB [97] aims to allow compositional transfer over a wider range of fine-grained stylistic constructs, including lexical, semantic, stylistic and thematic transfers.

**Rule constraints** While most research that is currently trying to address constrained text generation is focusing on the incorporation of pre-defined utility or lexical constraints, the satisfaction of rule based constraints is equally relevant, particularly when used to define format and syntactic conditions on the output. However, the lack of model expressiveness makes it challenging to incorporate rule based constraints into the loss function at training time. We encourage more effort in this direction likely to open a plethora of new possibilities in how constraints are specified, incorporated and satisfied in models particularly designed for constrained neural text generation.

**Evaluation of constrained text generation** In general, evaluation of text generative models is an open challenge. The field is missing robust automated evaluation metrics that correlate with human judgements across multiple dimensions of text quality. Evaluation of models for constrained text generation is currently done using the same flawed existing metrics commonly used in unconditional and conditional text generation evaluation, or in an informal way often times in the absence of a rigorous evaluation procedure. Human evaluation remains the gold standard way to assess text quality, however designing evaluation metrics tailored specifically at assessing whether generated texts meet desired constraints altogether with new benchmark datasets for the evaluation of constrained sequence generation are important next steps [78].

**Adversarial Attacks** Adversarial examples exploit vulnerabilities in text generation models and represent an active research area. Adversarial triggers in the form of input-agnostic sequences of tokens concatenated to any input dataset can trigger a pre-trained language models to produce biased, racist and discriminatory outputs even when these models are carefully fine-tuned and optimized against adversarial triggers [152]. Gradient-based adversarial trigger phrase search techniques are used to generate input prompts to a pre-language model that induce biases in the generated output and allows to study strategies for bias mitigation [141]. Constrained text generation models that are robust to adversarial attacks are needed for the beneficial use of machine learning and artificial intelligence technology in real world applications, as well as to mitigate any potential societal harms and biases associated with the deployment of large pre-trained language models.

While the above directions outline some of the most pressing research challenges associated with constrained text generation, it is nevertheless a non-exhaustive list of all research problems that need increased attention. Other important open challenges include the use of constrained text generation for personalized agents in a wide variety of contexts, such as in dialogue settings [164], and new benchmark datasets that are reflective of real-world constraints for both training/ fine-tuning and evaluating constrained text generation models.

**VIII. Conclusion**

In this work, we have presented the reasons why constrained natural language generation is an important, yet highly challenging and largely unsolved research problem. Our first contribution consists in clarifying the difference between the ambiguous use of unconditional, conditional and constrained terms in the natural language generation literature, and draw clear boundaries between these concepts by exemplifying instances of natural language generation tasks with their associated conditions and constraints. Among different paradigms of text generation, we consider constrained text generation to be particularly challenging (if not the most challenging), yet also extremely useful. We identify general reasons why constrained natural language generation deserves significant more attention in the research community, including the lack of model expressiveness in incorporating constraints into the objective function at training time, difficulty in constrained optimization algorithms, the lack of suitable evaluation metrics for robustly assessing, comparing model outputs and claiming success in constrained natural language generation, as well as the lack of constrained text generation datasets that are representative of a wide range of real-world constraints for training and fine-tuning these models. We then survey a representative body of recent literature on constrained text generation using neural networks, presenting the main approaches and methods used, as well as their limitations. We hope our work can serve as an informative guide for both researchers and practitioners to become familiar with the current methodology and main challenges, as well as an advocate for advancing the state-of-the-art in constrained natural language generation. We invite future work in solving the outlined challenges for better, useful, safer, robust constrained text generation and evaluation.

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