Controllable Text Generation for Open-Domain Creativity and Fairness

Nanyun Peng
Computer Science Department, University of California, Los Angeles
violtpeng@cs.ucla.edu

Abstract

Recent advances in large pre-trained language models have demonstrated strong results in generating natural languages and significantly improved performances for many natural language generation (NLG) applications such as machine translation and text summarization. However, when the generation tasks are more open-ended and the content is under-specified, existing techniques struggle to generate long-term coherent and creative content. Moreover, the models exhibit and even amplify social biases that are learned from the training corpora. This happens because the generation models are trained to capture the surface patterns (i.e., sequences of words), instead of capturing underlying semantics and discourse structures, as well as background knowledge including social norms. In this paper, I introduce our recent works on controllable text generation to enhance the creativity and fairness of language generation models.

1 Introduction

Natural language generation (NLG) tasks can be mapped into a spectrum based on their conditional entropy, i.e., the uncertainty of the output distribution given the inputs. One side of the spectrum is the low conditional entropy tasks, such as machine translation, abstractive summarization, and task-oriented dialogue systems, where the inputs largely determine the contents of the outputs. On the other side is the tasks that are open-ended and have high conditional entropy, such as story, poetry, or lyric generation given a title or a prompt, and open-domain dialogue systems (chit-chat), dubbed creative generation. In addition to be able to compose grammatical and fluent sentences to articulate given contents, these tasks usually also require extensive world and common sense knowledge, discourse-level coherence modeling to make sure the outputs are long-term coherent, sensible, and creative, making them especially challenging NLG tasks.

To tackle the challenges, my group has been working on several synergistic directions to push the frontier of open-domain (creative) generation, with a shared modeling theme of controllable text generation and applications to story, poetry, and dialogue response generation.

The first direction is to build hierarchical models that disentangle the content planning (plan out the structured representation of the content) from surface realization (convert the structured content to natural language sentences). This has three major benefits: i). It enhances the controllability of the generation through the plan and humans can more easily collaborate with the models on the plan-level to create novel contents. ii). It improves long-term coherence of the generation, since the compact plan representation helps the model to capture the high-level outline of the generation target, and iii). It enables the introduction of creativity on both the planning-level (e.g., better events and their temporal and causal relation modeling to introduce surprise) and the dictation-level (e.g., using figurative language to improve the writing). More details about this direction will be discussed in Section 2. Additionally, we develop fundamental models to support the controllable, hierarchical generation pipeline. i) We design insertion-based models that break the left-to-right generation order to better incorporate constraints/control factors (more details in Section 3). ii) We propose various constrained decoding algorithms to control the models. Finally, we have also been working on analyzing and reducing biases in open-domain generation (more details in Section 4).

2 Hierarchical Text Generation

Hierarchical text generation follows the plan-and-write [Yao et al., 2019] paradigm to first plan out the main content of the output, and then convert these structured plans into natural language texts (also called surface realization). The idea of content planning for text generation dates back to the late 70s [Meehan, 1976] with various plan representations. Prior works predominately rely on manually constructed or rule-based plans, which are either expensive to construct, or restricted to specific domains.

2.1 Automatic Content Plan Extraction

My group has been exploring the direction of learning content planning from existing corpora by using information extraction tools to extract “silver standard”
plan representations from data for models to learn planning [Yao et al., 2019; Goldfarb-Tarrant et al., 2020; Han et al., 2022]. Specifically, we have extensive works on extracting entities [Huang et al., 2019; Huang et al., 2021], entity relations [Peng et al., 2017; Hsu et al., 2022a], events [Ahmad et al., 2021; Hsu et al., 2022b], and event temporal relations [Han et al., 2019; Han et al., 2020; Han et al., 2021] from text corpora, to compose “silver standard” content plans for models to learn and generate novel plans during the test time.

2.2 Content Planning with Temporal Modeling, Literary Principles, and Surprise

While content plans have shown to be effective in improving the coherence of the generation [Yao et al., 2019], prior works also have shown that generated plans are much lower quality than the silver plans as they are usually repetitive, boring, and violate common sense and world knowledge [Martin et al., 2017; Yao et al., 2019; Fan et al., 2019]. To this end, we have been working on improving the planning model by introducing knowledge about literary principles [Goldfarb-Tarrant et al., 2020], event temporal knowledge [Han et al., 2022], and common sense knowledge. Specifically, we represent the plan generation model as a probabilistic model \( p(z|x) \) that is fitted by auto-regressive generative neural networks, where \( z \) represents the structured plan, \( x \) represents a given prompt. We modify the decoding objective to incorporate several rescoring models \( a \in A \) to re-rank the original, or “naive” plans generated by the graph generative model. These rescoring models bring the generated plan graph closer to each rescoring model’s specialty (such as relevance, coherence, and temporality). The modified decoding objective becomes:

\[
    f_A(x, z) = \sum_{i} -\log p(z | z < i, x) + \sum_{j} \lambda_j a_j(x, z, z_1, ..., z_m)
\]

where \( \lambda_j \) is the learned weight of the score given by \( a_j \).

What differs for each model \( a_j \) that specializes in a different rescoring aspect is the set of training data we generated to train the discriminators.

We also explored improving the interestingness of the generation, by introducing temporal diversity to the events, such as flashbacks that insert past events into current storylines as we commonly observe in novels and plays [Han et al., 2022]. It is challenging for machines to generate flashbacks as it requires solid understanding of event temporal order (e.g., feeling hungry (before) eat, not vice versa), and the creativity to arrange storylines so that earlier events do not always appear first in narrative order. Two major issues in existing systems exacerbate the challenges: 1) temporal bias in pre-training and datasets that leads to monotonic event temporal orders; 2) lack of explicit guidance that helps machines decide where to insert flashbacks. We address these issues by introducing temporal prompts to the structured plans to encode events and their pair-wise temporal relations ((before), (after) and (vague)) to guide how stories should unfold temporally. We showed that temporal prompts helped generate more interesting stories with flashbacks while maintaining textual diversity, fluency and temporal coherence.

2.3 Introducing Literary Aesthetics in Writing

Given a well-crafted plan, the other important component for the hierarchical generation is surface realization that converts plans into natural language sentences. The state-of-the-art pre-trained language models [Radford et al., 2019; Lewis et al., 2020] are capable of generating grammatical and fluent sentences, but they are usually plain and dull. To improve aesthetics in writing, we have explored incorporating figurative languages into the generation.

Figures of speech are literary devices that are commonly employed in narratives and stories [Boudens, 2005]. Proper usage of figurative languages can improve the effectiveness, interestingness, and enjoyment of communications [Stein et al., 2018]. However, the composition of figures of speech usually requires extensive contextual, common sense, and world knowledge [Justo et al., 2014; Yoshimura et al., 2015], which remains an open challenge for NLG. My group has been working on generating puns, similes, sarcasms, and metaphors [He et al., 2019; Chakrabarty et al., 2020a; Chakrabarty et al., 2020b; Chakrabarty et al., 2021; Stowe et al., 2021; Mittal et al., 2022], and incorporate them into story [Chakrabarty et al., 2020b] and poetry [Chakrabarty et al., 2021; Tian and Peng, 2022] generation to successfully improve the aesthetics of the writing.

3 Controllable Text Generation

One advantage of the hierarchical generation framework is the improved controllability of the generation through the plan – human writers can more easily collaborate with the models on the plan-level to control the generation contents. However, it is not straightforward to incorporate such controls in the state-of-the-art language generation models. The pre-trained auto-regressive language models [Radford et al., 2019; Lewis et al., 2020] usually generate sentences word by word from left to right, making the control of the generation process challenging.

3.1 Insertion-based Generation

Prior works [Fan et al., 2019; Yao et al., 2019] observed that fine-tune sequence-to-sequence models, while works decent for controllable language generate, cannot guarantee faithful incorporation of the plan. For example, we [Yao et al., 2019] showed that there are slightly less than 80% of storyline keywords (a form of plan) appeared in the generated story. [Fan et al., 2019] thus designed special verb-attention mechanism and incorporated copy mechanism to enhance the incorporation of the plans in the generation outputs. In light of these observations, we have been exploring a fundamentally different direction of controllable text generation framework – insertion-based text generation, or text infilling.

We proposed a general algorithm for efficient insertion-based text generation [Lu and Peng, 2021] to train a permutation language model with a delicate design of the permutations to reflect the insertion orders. To suit the non-monotonic
nature of the insertion-based generation process, a modified relative positional encoding mechanism is introduced such that each token is only aware of its relative position with respect to the generated partial sequence, but not the relative position with respect to the complete sequence. We showed the training efficiency, controllability, and the advantages of the model to generalize over partial observations. We plan to explore other applications for this novel efficient insertion-based NLG formulation and build a large-scale pre-trained insertion-based NLG model forlexically constrained text generation.

3.2 Controllable Decoding

There are also methods to control auto-regressive language models to leverage the powerful pretraining. They can be summarized into three major categories: fine-tuning, re-fact/retraining, and post-processing. The first two categories are usually inefficient considering the size of language models (billions of parameters). Therefore, my group has been mostly developing post-processing based models to control pre-trained auto-regressive language models. We have been pushing two lines of research: 1) adapting the decoding algorithm [Sheng et al., 2021] and 2) using auxiliary models to guide the decoding [Goldfarb-Tarrant et al., 2020; Chakrabarty et al., 2021].

4 Evaluating and Mitigating Biases in Open-Domain Text Generation

Evaluating open-domain generation is a challenging task as there are numerous plausible outputs given an input. Bias and fairness issues which are often subtle, should also be taken into consideration to guardrail the open-domain creative generation. We pioneered and have been actively exploring automatic evaluation of fairness aspects of the open-domain generation, including social stereotypes [Sheng et al., 2019; Sheng et al., 2020] and ad-hominem (a type of micro-aggression that is considered as toxic language) [Sheng et al., 2021] of open-domain generation. Some of our controllable text generation models are also developed under this context to reduce biases in generated texts [Sheng et al., 2020; Sheng et al., 2021].

5 Conclusion and Future Work

There are many exciting ongoing research directions in my group to push the frontier of natural language understanding and generation, with focused applications to creative and controllable text generation. Due to the space limit, I only briefly highlight three of them: 1) We are developing generation-based model for information extraction tasks. This can be applied to general natural language understanding, as well as better plan extraction for hierarchical generation. 2) We are trying to incorporate common sense knowledge into the control using common sense knowledge bases, semantic loss, and lexically constrained generation. 3) We are diving deeper into insertion-based text generation and pre-train the first insertion-based language model on large corpora.

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