Long Story Generation Challenge

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Abstract

We propose a shared task of human-like long story generation, *LSG Challenge,* that asks models to output a consistent human-like long story (a Harry Potter generic audience fanfic in English), given a prompt of about 1K tokens. We suggest a novel statistical metric of the text structuredness, GloVe Autocorrelations Power/ Exponential Law Mean Absolute Percentage Error Ratio (GAPELMAPER) and the use of previously-known UNION metric and a human evaluation protocol. We hope that *LSG Challenge* can open new avenues for researchers to investigate sampling approaches, prompting strategies, autoregressive and non-autoregressive text generation architectures and break the barrier to generate consistent long (40K+ word) texts.

1 Task Overview

The human-like long story generation (*LSG*) task asks models to output a consistent human-like long story (a Harry Potter generic audience fanfic in English), given a prompt of about 1K tokens. The text will be evaluated by automated metrics described in Section 3.1, and a human evaluation protocol described in Section 3.2.

2 Motivation

Autoregressive probabilistic large language models (LLMs) have become a cornerstone for solving every task in computational linguistics through few-shot learning (Brown et al., 2020) or prompt engineering (Sahn et al., 2021). Many users now interact with such models as ChatGPT, Claude, or Google Bard in chat setting regularly. However, these models still have many deficiencies. Despite the targeted effort, they can generate false information, propagate social stereotypes, and produce toxic language (Taori et al., 2023).

The LLM deficiency we particularly want to attack is their inability to produce a human-grade long text. Current autoregressive language models fail to catch long-range dependencies in the text consistently. Large language models such as GPT-3 (Brown et al., 2020), LLaMA (Touvron et al., 2023), ALPACA (Taori et al., 2023) push the boundary of “short text” rather far, but do not remove the problem. Commercial instruction-following language models such as ChatGPT, GPT-4, Claude and Google Bard are targeted at the use in a dialogue (and probably that is not for nothing). They generate a limited number of tokens per user input, and only generate further text after additional prompting. While the autoregressive window for commercial models at the time of writing reaches 32K tokens for OpenAI and even 100K tokens for Anthropic, which is a lot, it does not allow them to generate long coherent texts.

While relevance, consistency, fluency and coherence are easily achieved by the latest autoregressive generative models on short texts (under 10K tokens), all the current models fail when one tries to generate a long story in a single pass. Modeling long stories requires many additional abilities compared to short texts (Guan et al., 2022), including (1) commonsense reasoning regarding characters’ reaction and intention, and knowledge about physical objects (e.g., “river”) and abstract concepts (e.g., “irony”); (2) modeling discourse-level features such as inter-sentence relations (e.g., causality) and global discourse structures (e.g., the order of events); and (3) the generation coherence and controllability, which require both maintaining a coherent plot and adhering to controllable attributes (e.g., topics).

Mikhaylovskiy and Churilov (2023) have recently studied autocorrelations in long texts using pretrained word vectors. That allowed to study a wide range of autocorrelation distances in human-written and model-generated texts and show that the autocorrelations in human-written literary texts decay according to power laws on distances from 10 to 10K words independently from the language. On the other hand, the behavior of autocorrelations decay in generated texts is quantitatively and often qualitatively different from the literary texts. Large language models often exhibit Markovian (Markov, 1913) behavior with exponential autocorrelations decay.

Several authors have shown theoretically and empirically (Lin and Tegmark, 2017, Alvarez-Lacalle et al., 2006) that the power law autocorrelations decay is closely connected to the hierarchical structure of texts. Indeed, the hierarchical structure of, for example, Leo Tolstoy's War and Pease consists of at least 7 levels: the whole novel, books, parts, chapters, paragraphs, words, and letters. There are strong reasons to think that this structure reflects an important aspect of human thinking: people do not generate texts autoregressively. Writing a long text requires some thinking ahead, and going back to edit previous parts for consistency. This going back and forth can be reflected by navigating a tree-like structure. The autoregressive nature of the current state-of-the-art models does not reflect this, for example, S4 model (Gu et al., 2021) exhibits clear exponential autocorrelations decay (Mikhaylovskiy and Churilov, 2023).

We hope that this challenge can gain interest from the NLG community and advance sampling approaches, prompting strategies, autoregressive and non-autoregressive text generation architectures and other subfields of text generation.

3 Task Description

Formally, the task of LSG Challenge asks participants to provide a system that can output a consistent human-like long story (a Harry Potter generic audience fanfic at least 40K words long), given a prompt of about 1K tokens. A set of at least three dev prompts will be provided by organizers. The systems will be evaluated on a withheld test prompt. The prompts similar to the beginnings of human-written fan fiction will be developed from scratch specifically for the task.

	Power law MAPE	Exp law MAPE	GAPEL-MAPER
The Adventures of Tom Sawyer	0.21	0.55	0.38
The Republic	0.13	0.38	0.34
Don Quixote	0.20	0.44	0.45
War and Peace	0.09	0.42	0.21
Critique of Pure Reason	0.14	0.25	0.56
The Iliad	0.19	0.54	0.35
Moby-Dick or, The Whale	0.15	0.47	0.32
S4 generated text	0.062	0.050	1.24

Table 1: MAPE of power and exp law approximations of texts in English, and resulting GAPELMAPER

It is important to note that no copyright-eligible texts will be used in the shared task. The evaluation protocol below does not require using the original Harry Potter texts, and subjective evaluation relies on the fact that judges have read Harry Potter books/seen the films, but no factual knowledge of Harry Potter books is also required for the evaluation criteria below.

Given the open-ended and cutting-edge nature of the generation task and ongoing discussion on the best corpora and approaches to training LLMs, we feel that constraining the training set can be harmful to the task performance and participants are open to train their models on any dataset, as long as it is described in the system report.

We employ both automatic and human evaluation, described below to evaluate the quality of the texts.

3.1 GloVe Autocorrelations Power/ Exponential Law Mean Absolute Percentage Error Ratio (GAPEL-MAPER) Metric

Suppose we have a sequence of N vectors $V_i \in R^d, i \in [1, N]$. Autocorrelation function $C(\tau)$ is the average similarity between the vectors as a function of the lag $\tau = i - j$ between them. The simplest metric of vector similarity is the cosine distance $d(V_i, V_j) = \cos\angle(V_i, V_j) = \frac{V_i \cdot V_j}{\|V_i\|\|V_j\|}$, where $\cdot$ is a dot product between two vectors and $\| \quad \|$ is an Euclidean norm of a vector. Thus,

$$C(\tau) = \frac{1}{N-\tau}\sum_{i=1}^{N-\tau}\frac{V_i \cdot V_{i+\tau}}{||V_i||||V_{i+\tau}||}. \quad (5)$$

$C(\tau)$ ranges from -1 for perfectly anticorrelated sequence (for $\tau = 1$ and $d = 1$ that would be $1, -1, 1, -1$ etc.) to 1 for a perfectly correlated one (for $\tau = 1$ and $d = 1$ that would be $1, 1, 1, 1$ etc.).

A distributional semantic assigns a vector to each word or context in a text. Thus, a text is transformed into a sequence of vectors, and we can calculate an autocorrelation function for the text. Two distributional semantics approaches have been proposed for word-level autocorrelation computations: Alvarez-Lacalle et al. (2006) proposed a bag-of-words (BOW) model, and Mikhaylovskiy and Churilov (2023) have suggested the use of pretrained GloVe (Pennington et al., 2014) vectors. Unlike BOW, which only allows measuring long distance correlations, the latter approach allows to measure autocorrelations at any word distance starting with 1. Thus, we suggest using GloVe for autocorrelation measurement.

Mikhaylovskiy and Churilov (2023) have found that autocorrelations in long human-written texts decay according to a power law at ranges from 10 to 10K words. We suggest measuring the structuredness of a generated text by comparing how well the autocorrelations decay is approximated by power law and exponential law. To do so, one can compute autocorrelations in this range, approximate these points by a straight line in log-log and log-linear coordinates using the least squares regression and evaluate the goodness of fit of these regressions by MAPE (Mean Absolute Percentage Error). The ratio of these two errors constitute a metric we call GloVe Autocorrelations Power/Exponential Law Mean Absolute Percentage Error Ratio (GAPELMAPER):

$$\text{GAPELMAPER} = \frac{MAPE_{power}}{MAPE_{exp}}$$

GAPELMAPER less than 1 means that the autocorrelations decay according to a power law and the text is structured in a way. GAPELMAPER more than 1 means that the autocorrelations decay according to a exponential law and the text is unstructured. As a matter of example, we take Table 3 from Mikhaylovskiy and Churilov (2023) and compute GAPELMAPER in Table 1.

The metric proposed above does not require any gold standard, it is a statistical metric of the text itself. Thus, in terms of Guan and Huang (2020) it is an unreferenced metric.

3.2 UNION Metric

UNION is an unreferenced metric for evaluating open-ended story generation, proposed by Guan and Huang (2020). Built on top of BERT, UNION is trained to distinguish human-written stories from negative samples. The negative samples are programmatically constructed using Repetition, Substitution, Reordering and Negation Alteration.

3.3 Human Evaluation Approach

A single number is not enough to evaluate the quality of a long story. We adopt multiple human evaluation metrics to better measure model performance. Similarly to Kryscinski et al. (2019), we ask annotators to rate the texts across four dimensions:

1. relevance (of topics in the text to the expected ones),
2. consistency (alignment between the parts of the text),
3. fluency (quality of individual sentences), and
4. coherence (quality of sequence of sentences).

Additionally, extending (Guan et al., 2022), we ask annotators to rate

5. knowledge about physical objects (LLM generated failure example: “I was on shore in a boat; but I was not in the water. I was not in the water. I was in the water.”)
6. knowledge about abstract concepts (LLM generated failure example: “The twenty-eighth one is a twenty-eighth one. The twenty-nineteenth one is a twenty-eighth one. The twenty-ninth one is a twenty-ninth one. The twenty-tenth one is a twenty-tenth one.”)
7. causality (LLM generated failure example: “The first part was pretty easy. The second one, on the other hand, took a lot of practice. I had a lot of difficulty with the first one.”)
8. the order of events (LLM generated failure example: “This is the way all voyages of travel are done in all ages of the earth; they come to it and lay it down in the same fashion: — They get a wind, sail about awhile, and

gather what stores are sufficient for a week, or for one night's stay.")

Finally, extending Guan and Huang (2020) we ask annotators to rate

9. repeated plots (repeating similar texts)

A detailed evaluation manual will be developed as a part of the competition preparation and provided to judges, including a checklist conforming to suggestions of Howcroft et al., (2020).

Each text will be rated by 3 distinct judges with the final score obtained by averaging the individual scores. We plan to hire linguistics/philology students with English knowledge level at least C1 as the judges in at least two low-cost countries. Where possible, the judge assignment will be included into coursework. Small non-government/donation funding will be made available to cover judging expenses where the above approach is not possible.

3.4 Protocol

We propose the following schedule:

- **Phase 1** (from Sep, 2023): The shared task is announced at the INLG 2023 conference, and the data are available on the shared task website; participants can register to the task.
- **Phase 2** (from Dec, 2023): The leaderboard is open; participants can submit their systems to the organizers and the online leaderboard keeps updating the best performance using automatic evaluation metrics.
- **Phase 3** (from Mar, 2024): The submission is closed; organizers conduct manual evaluation.
- **Phase 4** (Jul, 2024): The LSG Challenge shared task is fully completed. Organizers submit participant reports and challenge reports to INLG 2024 and present at the conference.

For fairness and reproducibility, participants should specify what and how external resources are used in their system reports. In Phase 3, after the submission deadline, the organizers will start to evaluate summaries generated by final submitted models with the help from linguistic experts.

Please note that the above schedule can be modified accordingly when the schedule of INLG 2024 is released. The leaderboard and the detailed schedule will be announced on the shared task website.

4 Related work

Shaham et al. (2022) introduced SCROLLS, a suite of tasks that require reasoning over long texts. It includes earlier introduced works of Huang et al. (2021), Chen et al. (2022), Zhong et al. (2021), Dasigi et al. (2021), Kočiský et al. (2018), Pang et al. (2022), and Koreeda and Manning (2021). While all are related to long texts, none of these datasets and tasks asks to generate a long text.

Gehrmann et al. (2021) introduced GEM, a living benchmark for natural language Generation (NLG), its Evaluation, and Metrics. GEM provides an environment in which models can easily be applied to a wide set of tasks and in which evaluation strategies can be tested and consists of 11 datasets/tasks. Tay at al. (2020) proposed Long Range Arena, a suite of tasks consisting of sequences ranging from 1K to 16K tokens, encompassing a wide range of data types and modalities such as text, natural, synthetic images, and mathematical expressions requiring similarity, structural, and visual-spatial reasoning. None of these tasks asks to generate a long text as well.

Very recently Köksal et al. (2023) introduced the LongForm dataset, which is created by leveraging English corpus examples with augmented instructions. No evaluation protocol or competition is suggested in the cited paper.

On the unreferenced metrics front, Guan and Huang (2020) proposed UNION metric described in Section 3.2. Huang et al. (2020) proposed a metric dubbed GRADE, which stands for Graph-enhanced Representations for Automatic Dialogue Evaluation. Gao, Zhao, and Eger (2020) suggested SUPERT, which rates the quality of a summary by measuring its semantic similarity with a pseudo reference summary. Vasilyev, Dharnidharka, and Bohannon (2020) suggested BLANC that measures the performance boost gained by a pre-trained language model with access to a document summary while carrying out its language understanding task on the document's text.

The most similar effort to ours was most likely made by Guan et al. (2022), who proposed a story-centric benchmark named LOT for evaluating Chinese long text modeling. The benchmark aggregates two understanding tasks and two generation tasks. The authors constructed new datasets for these tasks based on human-written Chinese stories. Unlike our proposal, LOT benchmark is limited to texts hundreds of words long, and Chinese language.

5 Conclusion

We propose the LSG Challenge to address the task of long text generation, with the hope that it can open new avenues for researchers to investigate sampling approaches, prompting strategies, autoregressive and non-autoregressive text generation architectures and break the barrier to generate consistent long (40K+ token) texts, and the frontier of text generation can be pushed further.

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