Factuality Enhanced Language Models for Open-Ended Text Generation

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Abstract

Pretrained language models (LMs) can easily generate text with nonfactual information. In this work, we measure and improve the factual accuracy of large-scale LMs for open-ended text generation. We design the FACTUALITYPROMPTS test set and metrics to measure the factuality of LM generations. Based on that, we study the factual accuracy of LMs with parameter sizes ranging from 126M to 530B. Interestingly, we find that larger LMs are more *factual* than smaller ones, although a previous study suggests that larger LMs can be less truthful in terms of *misconceptions*. In addition, popular sampling algorithms (e.g., top-p) in open-ended text generation can reduce the factuality due to the "uniform randomness" introduced at every sampling step. We propose a *factual-nucleus* sampling algorithm that dynamically adapts the randomness to improve the factuality of generation while maintaining quality. Furthermore, we analyze the inefficiencies of the standard training method in learning correct associations between entities from factual text corpus (e.g., Wikipedia). We propose a *factuality-enhanced* training method that uses TOPICPREFIX for better awareness of facts and sentence completion as the training objective, which vastly reduces the factual errors from LMs.

1 Introduction

Large-scale pre-trained language models (LMs) have demonstrated impressive natural language generation results [1–4]. However, the generative LMs (e.g., GPT-3) are solely trained to model the statistical correlations between subword tokens [5], and have limited capability to generate factually accurate text as illustrated in Table 1. As a result, there are increasing concerns about the nonfactual generations from large-scale pre-trained LMs [e.g., 6, 7], which needs to be adequately addressed for their safe deployment in real-world applications, e.g., content creation [8] and dialogue [9].

In previous studies, different metrics and methods have been proposed to measure and improve the factual accuracy of language generation within different tasks [10], including text summarization [e.g., 11–14], question answering [e.g., 15–17], and table-to-text generation [e.g., 18, 19]. However, these works focus on the factuality (or faithfulness) of the *fine-tuned* LMs for particular downstream tasks (i.e., factual consistency between source and target text). Little exploration is made to address the factual errors in *pretrained* LMs for general-purpose open-ended text generation, where the goal is to generate a coherent continuation from the given context (e.g., the use cases from GPT-2).

One of the popular methods for enhancing generation factuality is to incorporate external knowledge sources [20–22]. Structured knowledge bases and graphs have been utilized for grounded text generation for years [e.g., 23, 24], where the LMs are trained to select and copy relevant facts from external knowledge sources. In contrast to the sizeable online text for pretraining, the structured knowledge graphs only encode a limited amount of knowledge as they require expensive human annotations for high-quality construction. A method that can directly leverage plain text knowledge (e.g., Wikipedia,

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Table 1: Example of continuations from the 530B LM with greedy decoding and nucleus sampling $p = 0.9$, along with the continuation from factuality-enhanced 530B LM with *factual-nucleus sampling*. Red represents nonfactual, green represents factual, and ~~strikethrough~~ represents repetition. See Appendix C for more examples.

[Factual Prompt] One of lung cancer's symptoms is shortness of breath.
[Greedy] The American Cancer Society estimates that more than 228,000 people will be diagnosed with lung cancer in the United States this year.\n\n ~~The American Cancer Society estimates that more than 228,000 people will be diagnosed with lung cancer in the United States this year.\n\nThe American...~~
[p=0.9] That would make an oxygen mask one of the more popular treatments for this devastating disease. It helps ease breathing and give patients back their strength. Learn more here.<|endoftext|>"
[Ours] Other symptoms include coughing (including coughing up blood), chest pain, hoarseness, weight loss, and loss of appetite. The symptoms of lung cancer may resemble those of a bad cold or pneumonia. A chest x - ray is necessary to confirm the diagnosis. The diagnosis is usually confirmed by biopsy, in...
[Non-Factual Prompt] Cancer can be prevented by drinking too much alcohol.
[Greedy] \nCancer can be prevented by eating too much red meat.\n\n~~Cancer can be prevented by eating too much~~ sugar.~~\n\nCancer can be prevented by eating too much~~ fat.~~\n\nCancer can be prevented by eating too much~~ processed food.~~\n\nCancer can be~~...
[p=0.9] More than 90% of hepatocellular carcinoma is associated with alcohol use.\n\nAbout 9 percent of cancers can be prevented if we don't eat more than 1.5 ounces of processed meat each day.\nDiet...
[Ours] Cancer is often treated with some combination of radiation therapy, surgery, chemotherapy and targeted therapy. Pain and symptom management are an important part of care. Palliative care is particularly important in people with advanced disease. The chance of survival depends on the type of cancer and...

encyclopedia books, peer-reviewed publications) would be a desirable form of factuality enhancement as it can remove the human annotation bottleneck and easily scale up the amount of injected knowledge. Augmenting LM with an information retrieval (IR) system is one possible solution to leverage textual facts, however, at the cost of additional complexity and resource overhead to the model [25–27, 21, 9]. Therefore, we explore an IR-free method that enhances the innate factuality of LMs by further training the pretrained LM on a factually rich plain-text corpus.

In this work, we focus on measuring and improving the factuality of large-scale pre-trained language models (LMs) for open-ended text generation. Specifically, we make the following contributions:

1. We build the benchmark and metrics to measure the factual accuracy of pre-trained LM for open-ended text generation. Based on that, we systematically study the factual accuracy of LMs with parameter sizes ranging from 126M to 530B and find that large LMs have higher factual accuracy than smaller ones.
2. We study the decoding algorithms of LM in terms of factual accuracy. We unveil that the popular nucleus sampling algorithm [28] for open-ended text generation can easily mix up different named entities or randomly fabricate information due to the "uniform randomness" introduced at every decoding step. We propose *factual-nucleus* sampling algorithm that promotes generation factuality while maintaining the quality and diversity.
3. We explore training methods that can effectively leverage text corpus with rich facts (e.g., Wikipedia). We find that directly continuing the pre-training of LM on factual text data [29] does not guarantee the improvement of factual accuracy. We propose *factuality-enhanced* training to address the underlying inefficiencies of this baseline. Our method consists of i) an addition of a TOPICPREFIX that improves the awareness of facts during training, and ii) a sentence completion task as the new objective for continued LM pretraining [e.g., 29].
4. We demonstrate that the factual accuracy of large-scale LMs (up to 530B) can be significantly enhanced (e.g., NE_{Er} error reduced from 33.3% to 14.5%) after applying the proposed *factuality-enhanced* training with *factual-nucleus* sampling algorithm.

We organize the rest of the paper as follows. We discuss related work in § 2 and present our benchmark setup with evaluation protocol in § 3. We study the factual accuracy of LMs with respect to model size, prompt type, and choice of decoding algorithm in § 4. After that, we present *factual-nucleus* sampling algorithm in § 5, and *factuality-enhanced* training in § 6. We conclude the paper in § 7.

2 Related Work

Factuality vs. Model Size Lin et al. [30] propose the TruthfulQA benchmark to measure the falsehood generations from different sized LMs. The result suggests that bigger LMs pre-trained on

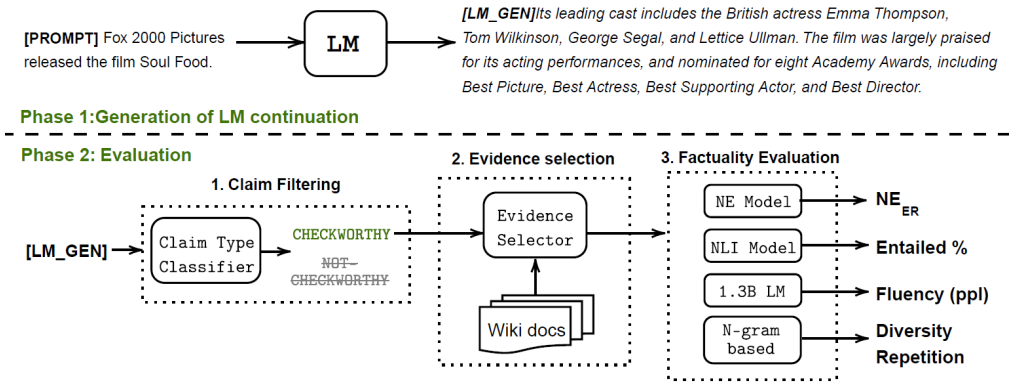

Figure 1: Illustration of our evaluation framework

web text are generally less truthful than smaller ones in terms of false belief or misconception. At first glance, this is contradictory to our observations, however, our work actaully focuses on different knowledge to TruthfulQA work. The TruthfulQA benchmark focuses on conceptual knowledge, while our benchmark focuses on factual knowledge [31]. [1] Large LMs can be good at recalling factual knowledge given substantial pre-training corpus, suggested by previous studies on LM's parameteric knowledge [32], but there still remains room for improvement for reasoning conceptual knowledge [33, 34].

Parametric Factual Knowledge There is a line of work addressing the factual errors in the parametric knowledge of LMs that is acquired from pretraining corpus [35–37]. The correctness of the parametric knowledge is commonly tested in cloze-style question answering format [32] (e.g., Person X is born in __) Efforts are made to fine-tune the pre-trained LM to "inject" more knowledge and improve its ability to answer factual questions without consulting external knowledge source [16]. Moreover, some work attempts to edit and fix the factual errors [38–40]. However, it is unclear if the improvement of fine-tuned LM for QA-style task can help to mitigate factual errors in open-ended text generation task.

Hallucination in downstream NLG tasks There are active efforts to reduce the factual errors or unfaithfulness of task-specific LMs fine-tuned for various downstream NLG tasks such as umma-rization [41–47], data-to-text [48, 49, 19, 50–52] and dialogue system [53–57]. In contrast to these works. we focus on general purpose LM for open-ended text generation task.

Human-in-the-loop Human feedback or demonstrations are valuable to improve the factual accuracy of LMs. For example, InstructGPT [58] fine-tune the LMs with collected human feedback for a truthful generation. WebGPT [7] is trained to cite its sources when it generates output, thus allowing humans to evaluate factual accuracy by checking whether a claim is supported by a reliable source.

3 FACTUALITYPROMPTS and Evaluation Metrics

Our goal is to automatically measure and evaluate the factuality of large-scale pre-trained language models (LMs) for open-ended text generation. Factuality refers to being coherent to provided ground-truth knowledge sources in NLP [10]. The biggest challenge of evaluating factuality for open-ended text generation is associated with locating the ground-truth knowledge from the massive amount of world knowledge. Evaluating open-ended text generation can be challenging due to the lack of ground-truth references for generation [59, 28]. In this study, we scope our ground-truth knowledge source to be Wikipedia because this will help simplify the evaluation setup. Note that Wikipedia is one of the most commonly-used, accessible, large-scale, good quality, unstructured knowledge sources. Our proposed methods can easily generalize to other knowledge sources in plain text (e.g., arXiv papers, medical reports, reliable newspapers).

Our evaluation framework consists of the following steps, as illustrated in Fig 1. In phase 1, LM generates the continuation using test prompts (§3.1). In phase 2, we first identify check-worthy

[1] According to Krathwohl [31], knowledge can be categorized into four types: i) factual knowledge, ii) conceptual knowledge, iii) procedural knowledge, and iv) metacognitive knowledge.

continuations [2], which refers to the generations that do contain facts and require factuality evaluation. This step is necessary as open-text generation does not always generate text that contains facts such as personal opinions and chitchat-style text (e.g., "I like eating an apple!"). Then, we prepare relevant ground-truth knowledge required for factual verification of check-worthy continuations (§3.2). Lastly, we obtain the factuality measures and the quality measures (§3.3).

3.1 FACTUALITYPROMPTS Testset

We design our test prompts, FACTUALITYPROMPTS, that follows a similar setup as in RealToxicityPrompts [60], which has *toxic* and *nontoxic* prompts to evaluate the toxicity of LM continuations. FACTUALITYPROMPTS consists of *factual* and *nonfactual* prompts that allow us to study the impact of prompts' factuality on the LM continuation; this simulates the real-world scenario where input texts are not guaranteed to be factual.

Since high quality fact-related data collection requires a lot of human efforts, we instead utilize a well-established fact-related dataset, FEVER [61], to construct our factual and nonfactual prompts. FEVER is a fact-checking dataset consisting of claims that are SUPPORTED, REFUTED or unverifiable (NOTENOUGHINFO) by Wikipedia documents. These claims are created by annotators who were asked to alter or paraphrase the sentences from Wikipedia. We leverage the SUPPORTED and REFUTED claims from FEVER validation set [3] as the factual and nonfactual prompts, respectively. To further ensure the quality of the test set, we filter out claims that are not appropriate to serve as prompts – e.g., extremely short claims that are not enough to provide any context to the LM. The data statistics after filtering is reported in Appendix F. We will release the constructed FACTUALITYPROMPTS for future research.

3.2 Ground-Truth Knowledge Preparation

To evaluate the factuality of a given generation, we need to prepare relevant ground-truth knowledge. The required ground-truth knowledge can be either document-level or sentence-level, depending on the type of factuality metrics (discussed in §3.3). The correctness of factuality evaluation is crucially dependent on the correctness of the ground-truth knowledge. To ensure that our factuality evaluation is not distorted by the irrelevant provision of ground-truth knowledge, we do the following:

For **document-level** ground-truth knowledge, we directly use the Wikipedia document annotation provided in the FEVER dataset. This way, we can mitigate any potential error from automatic document retrieval. For **sentence-level** ground-truth knowledge, we do automatic sentence selection by using two different method to maximize the chance of recalling the relevant ground-truth knowledge. We treat the generated text as query q and Wikipedia sentences as a pool of candidates $C = \{c_1, c_2, c_3, ...c_N\}$ where N is the number of sentences in the Wikipedia document. One ground-truth sentence is retrieved by obtaining TFIDF vector representations of q and C and selecting the c_i with the highest cosine similarity with the q. Another is retrieved by obtaining the contextual representation of q and C using SentenceTransformer [62] and selecting the c_j with the highest cosine similarity.

3.3 Evaluation Metrics

We adapt commonly used metric designs from the hallucination literature that are shown to have good correlation with human judgement [10]: named-entity (NE) based metric and entailment based metric. Each metric captures a different aspect of factuality, so we use both metrics for better understanding of factuality.

Hallucinated NE Error Named entities are one of the core building blocks of "fact", so NE-related metric design is one of the common choices in literature [63, 64, 10]. In this work, we specifically adopt the NE-based metric [64] that is designed with an assumption that a model is hallucinating (tending to make factual errors) if it generates a NE that does not appear in the ground-truth knowledge source.

We define our NE-based metric to be: $\text{NE}_{\text{ER}} = |\text{HALLU}_{\text{NE}}| \ / \ |\text{ALL}_{\text{NE}}|$ where ALL_{NE} is the set of all the NEs detected in the LM generation, and HALLU_{NE} is subset of NE_{All} that does not appear in the

[2] Refer to Appendix D for details

[3] The testset is not publicly released and can only be accessed through the FEVER workshop submission site. Therefore, it is common practice to leverage validation set instead.

Table 2: The factuality of LMs with different parameter size from 126M to 530B. NE_{ER} refers to the named-entity error, Entail refers to entailment ratio, Div. refers to distinct 4-grams, and Rep. refers to repetition. ↑ means the higher the better, and ↓ means the lower the better.

Size	Decode	Factual Prompt				Nonfactual Prompt			
		NE_{ER}↓	Entail↑	Div.↑	Rep.↓	NE_{ER}↓	Entail↑	Div.↑	Rep.↓
126M	p=0.9	63.69%	0.94%	0.90	0.58%	67.71%	0.76%	0.90	0.38%
	greedy	48.55%	8.36%	0.03	59.06%	54.24%	6.25%	0.03	59.90%
357M	p=0.9	56.70%	2.01%	0.87	0.55%	60.80%	1.42%	0.88	0.35%
	greedy	43.04%	14.25%	0.03	45.18%	46.79%	9.89%	0.04	46.30%
1.3B	p=0.9	52.42%	2.93%	0.88	0.24%	56.82%	2.04%	0.89	0.25%
	greedy	39.87%	12.91%	0.05	33.13%	45.02%	8.75%	0.05	36.20%
8.3B	p=0.9	40.59%	7.07%	0.90	0.11%	47.49%	3.57%	0.91	0.08%
	greedy	28.06%	22.80%	0.07	19.41%	32.29%	15.01%	0.07	13.26%
530B	p=0.9	33.30%	11.80%	0.90	0.13%	40.49%	7.25%	0.92	0.08%
	greedy	**20.85%**	**31.94%**	0.08	15.88%	27.95%	19.91%	0.08	16.28%

ground-truth Wikipedia document. Note that evaluating NE_{ER} requires document-level ground-truth. To ensure the quality of the metric, we also take the same precautions used by [64]. For named entities consisting of multiple words, partial n-gram overlaps are also treated as a "match". This ensures we can address the shortened form of named entities – e.g., "Barack Hussein Obama II" vs. "Obama". Note that stopwords (e.g., the, a) are not considered in the partial n-gram overlaps. The named entities are detected using a publicly available pre-trained NE detection model from Spacy [4].

Entailment Ratio Textual Entailment (or natural language inference) is a task of determining whether a hypothesis is entailed by, refuted by, or neutral to a given premise [65]. Entailment-based metrics are based on the rationale that factual generation will be entailed by the ground-truth knowledge [66, 11, 67, 68, 10].

We define the entailment ratio as: Entail= $|\text{ENTAIL}_{\text{gen}}|$ / $|\text{ALL}_{\text{gen}}|$, where ALL_{gen} is set of all generations, and $\text{ENTAIL}_{\text{gen}}$ is the set of generations that are entailed by a entailment model. To obtain the entailment scores, we leverage a pretrained entailment model that is publicly available; a RoBERTa [69] model fine-tuned on MNLI [70] dataset. Entail requires sentence-level ground-truth because only a few Wikipedia sentences are relevant to specific factual information in a given generation. For example, "Barack Obama was born in Hawaii" is only relevant to the Wikipedia sentence that mentions his birth location.

Generation Quality Evaluation We evaluate the generation quality on three aspects: *i) Fluency* is measured by the mean perplexity of generated continuations evaluated on a larger pretrained LM." *ii) Diversity* is an important characteristic of LM that makes the generation more interesting and engaging – it is bland and boring to always generate same texts. It is measured using the mean number of distinct n-grams (we report 4-gram), normalized by the length of text [71, 72] among the 10 generations for each prompt (i.e., in total, 160000 generations to evaluate the diversity of each method). *iii) Repetition* is a common form of degeneration. We measure the number of repetitive substrings that get generated at the end of the generations by using the publicly available metric code from Holtzman et al. [28].

4 Factuality Analysis of Pretrained LMs

In this section, we perform a factuality analysis of LMs from three aspects: *i)* model size, *ii)* prompt type and *iii)* decoding algorithm.

Model Size Researchers have observed the trend of larger LMs outperforming smaller ones in various downstream tasks [73, 3, 2]. However, contradicting to these general observations, recent studies suggest that larger LMs are actually less truthful in human misconceptions [30] and zero-shot fact-checking performance tend to stagnate with LM scaling [6]. We study the factuality of LMs with a range of parameter sizes (126M, 357M, 1.3B, 8.3B, 530B) to understand whether such surprising trend also applies to open-ended text generation task. As shown in Table 2, generation factuality does

[4] https://spacy.io/

improve with parameters scaling, e.g., NE_{ER} drops from 63.99% to 33.30% when parameter size scales up from 126M to 530B.

Prompt Type Prompts provided to the LM are known to significantly affect the quality and characteristics of LM continuations [74, 60]. We use our factual and nonfactual prompts to test the behavior of LMs. Results in Table 2 show that both factual and nonfactual prompts can lead to nonfactual generations, although factual prompts always result in less nonfactual generations. Interestingly, the performance gap between factual and nonfactual prompts gets more prominent as the model size increases (4% to 7% in NE_{ER} as parameter size increases from 126M to 530B). This could be because the larger LM better understands the prompts and can imitate the factual or nonfactual prompts in the continuations.

Decoding Algorithm We investigate the choice of decoding algorithms and their impact on the factual accuracy of generations. In particular, we compare two representative decoding algorithms that are *greedy decoding* (i.e., maximize generation likelihood) and *nucleus sampling* [28]. Nucleus sampling (a.k.a. top-p decoding) samples only from the top subword candidates with total probability p. It is a popular decoding algorithm for open-ended text generation because it solves many well-known degeneration problems of the greedy decoding algorithm. However, our results (Table 2) shows that top-p decoding under-performs greedy decoding in terms of factuality, although it achieves high generation diversity and quality. This intuitively makes sense because the sampling-based word choice in nucleus sampling can be seen as adding "randomness" to encourage diversity, which as a result, can lead to factual errors. Note that the factuality of a sentence can be easily altered by one-word choice. For example, "Barack Obama was born in 1961" can turn nonfactual if "1961" is changed to "1962". In the same sense, greedy decoding is more factual because its way of choosing the word with the highest probability minimizes randomness and maximizes the utilization of parametric knowledge of LM [32, 35]. However, greedy decoding achieves such factuality at the cost of generation diversity and quality.

Error Types We conduct a qualitative analysis of the factual errors from greedy generation of 530B LM, to understand what are the remaining errors when the randomness from decoding choice is strictly restricted. The two notable error types were:

- **Named Entity Mix-up**: Mixing up similar types of the named entity. For example, LM generated "*The movie is based on the novel of the same name by Gayle Forman.*" about a film called "*The Best of Me*". However, the correct author's name is "Nicholas Sparks", not "Gayle Forman". Note that Gayle Forman is also an American young adult fiction author who writes similar type of novels as Nicholas Sparks.
- **Fact Invention:** Inventing random new facts. For example, "*Samuel Witwer's father is a Lutheran minister*."

Both error types can be viewed as wrong associations of entities that appear at different parts of the training corpus with similar context. Such behavior is unsurprising because these LMs are uniformly trained with the next subword token prediction objective instead of a fact-related objective.

5 Factual-Nucleus Sampling

5.1 Method

From our analysis in §4, we observed that the sampling algorithm is a double-edged sword that contributes to both factual errors and repetitions. We hypothesize that sampling is more harmful to factuality when it is used to generate the latter part of a sentence than the beginning of a sentence. There is no preceding text at the start of a sentence, so it is safe for LM to generate anything as long as it is grammatical. However, as the generation proceeds, the context and premise become more determined, and fewer word choices can make the sentence factual. Given the example "*Samuel Witwer's father is a Lutheran minister*", the beginning of the sentence "*Samuel Witwer's father is*" is not nonfactual. However, the continuation of "*Lutheran minister*" makes the sentence nonfactual. Therefore, we propose a new sampling algorithm, *factual-nucleus sampling*, that dynamically adapt the "nucleus" p, along the sentence with the following techniques:

- **λ-decay**: Given that top-p sampling pool is selected as a set of words whose cumulative probability exceeds p, we gradually decay the p value with decay factor λ at each generation step to reduce the "randomness" through time.

Table 3: **1.3B** LM results with different decoding algorithms. NE_{ER} refers to named-entity error, Entail refers to Entail, Div. refers to distinct 4-grams, and Rep. refers to repetition. ↑ means the higher, the better, and ↓ means the lower, the better. p, λ and ω are nucleus probability, decay factor, and decay lowerbounds respectively.

Decoding	**Factual Prompt**				**Nonfactual Prompt**			
	NE_{ER}↓	Entail↑	Div.↑	Rep.↓	NE_{ER}↓	Entail↑	Div.↑	Rep.↓
Greedy	39.9%	12.9%	0.05	33.1%	45.0%	8.8%	0.05	36.2%
Top-p 0.9	52.4%	2.9%	0.88	0.2%	56.8%	2.0%	0.89	0.3%
p | λ	Top-p + λ-decay							
0.9 | 0.9	41.1%	10.8%	0.43	30.7%	45.7%	6.8%	0.47	34.5%
0.9 | 0.5	39.9%	13.0%	0.08	33.1%	44.9%	9.1%	0.09	35.9%
p | λ	Top-p + λ-decay + p-reset							
0.9 | 0.9	41.5%	10.3%	0.52	10.3%	45.4%	6.3%	0.57	9.1%
0.9 | 0.5	39.3%	12.8%	0.34	17.8%	44.5%	8.4%	0.45	18.9%
p | λ | ω	Top-p + λ-decay + p-reset + ω-bound (*factual-nucleus sampling*)							
0.9 | 0.9 | 0.3	42.1%	10.1%	0.55	7.1%	46.5%	5.6%	0.59	6.4%
0.9 | 0.5 | 0.3	41.0%	12.2%	0.47	13.0%	46.0%	7.0%	0.51	12.7%
0.9 | 0.9 | 0.2	41.7%	9.9%	0.52	8.6%	45.6%	6.2%	0.56	7.6%
0.9 | 0.5 | 0.2	39.3%	12.8%	0.38	16.1%	45.2%	7.8%	0.42	16.9%

- **p-reset**: The nucleus probability p can quickly decay to a small value after a long generation. So, we reset the p-value to the default value at the beginning of every new sentence in the generation (we identify the beginning of a new sentence by checking if the previous step has generated a full-stop). This reduces unnecessarily sacrifice of diversity of any long generations.
- **ω-bound**: If λ-decay is applied alone, the p-value would quickly become too small to be equivalent to greedy decoding and hurt diversity. To overcome this, we introduce a lower-bound ω to limit how far p-value can be decayed.

In *factual-nucleus sampling*, the nucleus probability p_t to generate the t-th token for each sentence is,

$$p_t = \max\{\omega,\ p \times \lambda^{t-1}\},$$

where λ is the decay factor for top-p probability, and ω lower bounds the decay of probability.

5.2 Result

We report our decoding experimental results with 1.3B LM [5] in Table 3. Additions of λ-decay helps improve top-p 0.9 factuality result – for instance, with decay rate λ=0.5, there is 12.5% drop in NE_{ER} and 10.1% gain in Entail. However, this affects the diversity and repetition to become similar to greedy decoding. Incorporation of p-reset helps mitigate this diversity issue without losing much in factuality metric. The effect is more drastic for the λ=0.5 option, where it achieves 0.26 gains in diversity metric with negligible changes in factuality scores. By also adding ω-bound, we obtain the anticipated factuality performance (i.e., similar to greedy decoding), with great improvement in generation quality over greedy; with p=0.9, λ=0.9, ω=0.3, we achieve $\times$11 improvement in diversity and $\times$4.6 improvement in repetition over greedy. Although our factual-nucleus sampling still under-performs top-p 0.9 in terms of diversity, we believe this is a reasonable trade-off to improve the factuality of LM for factually sensitive open-ended generation tasks. Moreover, our proposed decoding does not harm the sentence fluency; its perplexity do not exceed the perplexity of top-p. Refer to Appendix H for full perplexity results.

6 Factuality-enhanced Continued Pretraining

This section introduces our factuality-enhanced method for continued pretraining of LMs [29]. We first introduce the TOPICPREFIX for better awareness of facts. Then, we present the sentence completion task as the training objective.

[5] 1.3B LM is mainly used as it is big enough to have good learning capacity yet not too resource expensive.

Table 4: Results for factuality enhanced training. The decoding settings are formatted as: nucleus p value, decay rate λ, lower-bound ω

Decoding	Factual Prompt				Nonfactual Prompt			
(p | λ | ω)	NE_{ER}↓	Entail↑	Div.	Rep.	NE_{ER}	Entail	Div.	Rep.
Vanilla Pretrained LM (1.3B)								
0.9	52.4%	2.9%	0.88	0.2%	56.8%	2.0%	0.89	0.3%
0.9 | 0.9 | 0.3	42.1%	10.1%	0.55	7.1%	46.5%	5.6%	0.59	6.4%
Factual Domain-Adaptive Training with Wikipedia (1.3B)								
0.9	52.5%	2.8%	0.85	0.2%	55.8%	2.2%	0.86	0.1%
0.9 | 0.9 | 0.3	42.7%	7.1%	0.51	7.2%	48.2%	4.9%	0.56	6.0%
TOPICPREFIX (1.3B)								
0.9	34.4%	4.2%	0.84	0.3%	36.2%	2.7%	0.85	0.2%
0.9 | 0.9 | 0.3	27.6%	8.7%	0.43	8.0%	30.5%	6.1%	0.47	6.9%
TOPICPREFIX + SC_{ROOT} (1.3B)								
0.9	32.5%	6.7%	0.83	1.2%	34.3%	4.6%	0.84	1.1%
0.9 | 0.9 | 0.3	24.7%	15.8%	0.40	13.6%	27.6%	9.1%	0.44	13.7%
TOPICPREFIX + SC_{RANDOM} (1.3B)								
0.9	32.0%	7.9%	0.81	1.2%	34.2%	5.5%	0.83	1.1%
0.9 | 0.9 | 0.3	23.6%	17.6%	0.39	14.2%	26.9%	9.3%	0.42	13.2%
TOPICPREFIX + SC_{HALF} (1.3B)								
0.9	31.6%	7.6%	0.81	1.4%	33.5%	5.1%	0.83	1.5%
0.9 | 0.9 | 0.3	23.6%	17.4%	0.38	14.4%	27.2%	10.2%	0.42	13.1%
Vanilla Pretrained LM (530B)								
0.9	33.3%	11.8%	0.90	0.1%	40.5%	7.25%	0.92	0.1%
TOPICPREFIX + SC_{HALF} (530B)								
0.9	18.3%	19.3%	0.68	0.1%	21.7%	13.7%	0.68	0.1%
0.9 | 0.9 | 0.3	**14.5%**	**25.5%**	0.33	0.2%	**17.7%**	**20.0%**	0.33	0.1%

6.1 Prepending TOPICPREFIX

Unstructured factual knowledge typically exists at a document level (i.e., a group of factual sentences about an entity or things). This means that sentences can contain pronouns (e.g., she, he, it), making these sentences factually useless standalone. To illustrate with a concrete example from Barack Obama's Wikipedia page, "He previously served as a U.S. senator from Illinois from 2005 to 2008" cannot be a useful standalone fact because it is unclear who "He" is. It is essential to know the reference of the individual sentence-level facts.

If LMs could be trained at the full-document level, this would not be an issue. However, due to the GPU memory limit for long documents and computation efficiency, it is common to chunk documents before feeding them into the LMs during training. This causes the "fragmentation" of information and leads to wrong associations of entities that appear in independent documents with similar contexts. As a remedy, we propose to prepend TOPICPREFIX to sentences in the factual documents to make each sentence serve as a standalone fact. In our experiments, we mainly utilize Wikipedia documents as the factual corpus and the Wikipedia document name as the TOPICPREFIX .

6.2 Sentence Completion Loss

We propose a sentence completion loss to address the incorrect association learned between entities. To explain our rationale behind this, let us recall our nonfactual example from §5: "*Samuel Witwer's father is a Lutheran minister*". This sentence became nonfactual because LM failed to generate factually correct information after "*Samuel Witwer's father is*". In other words, LM failed to accurately *complete* the sentence given the already generated tokens. One reason is that the LM is uniformly trained to predict each subword token within the sentence, when ensuring the correct prediction at the

latter section of sentence is more critical for factuality. Therefore, we construct a sentence completion loss, which makes the LM focus on predicting the subwords later in the sentence. For implementation, we determine a pivot t for each sentence, and then apply zero-masking for all token prediction losses before t. We emphasize that this loss masking is different from the input token masking applied in BERT [73] or BART [75], and the LM is still trained in an autoregressive manner. Note that many BART-based summarization models are known to still suffer from factual errors, suggesting that masked prediction at the encoder level may not effectively transfer well to text generation. We demonstrate that the proposed masked prediction task are really effective for reducing factual errors when it is combined with TOPICPREFIX .

In this work, we explore three strategies to determine the pivot t from simple to complex:

- SC_{HALF}: pivot $t = 0.5\times$ sentence-length.
- SC_{RANDOM}: random pivot, e.g., $t \sim \text{uniform}[0.25, 0.75]\times$ sentence-length.
- SC_{ROOT}: pivot $t =$ position of ROOT (relation) after dependency parsing.

Surprisingly, according to our results, the simplest SC_{HALF} performs on par with the complex ones.

6.3 Results

Experimental results for our factuality-enhanced continued pretraining are reported in Table 4, and experimental setups are reported in Appendix E.

Ineffectiveness of Domain Adaptive Training The pre-training corpus of LM contains both factual texts (e.g., Wikipedia) and nonfactual texts (e.g., rumors, fake news). The nonfactual domain of the training corpus could be the problem. Thus, we conduct a baseline experiment that does domain-adaptive training with strictly factual domain text only (i.e., Wikipedia). Interestingly, we discover that domain-adaptive training has minimal impact on the generation factuality.

Effect of TOPICPREFIX Continued pre-training of 1.3B LM with TOPICPREFIX preprocessed Wikipedia alone can already improve the factuality, especially in terms of NE_{ER}. For example, it reduces the $\text{NE}_{\text{ER}}$from 42.1% to 27.6% when we use the factual-nucleus decoding (0.9 | 0.9 | 0.3), which even outperforms the 1.3B with greedy decoding (NE_{ER}: 27.6% vs. 39.9%) with much less repetition (8.0% vs. 33.1%).

Effect of Sentence Completion Loss The proposed sentence completion loss further helps to improve the factuality, especially for the Entail. For example, when one uses factual-nucleus decoding on trained 1.3B model, TOPICPREFIX + SC_{HALF} can further improve Entail from 8.7% to 17.4% than TOPICPREFIX alone, while reducing $\text{NE}_{\text{ER}}$from 27.6% to 23.6%. Note that the results show consistent improvement across different pivot selection strategies, suggesting that the sentence completion loss is robust. In particular, the simplest SC_{HALF} performs as good as others or even better in terms of several metrics. Thus we recommend it as the default option.

530B vs 1.3B As expected, our method on 530B LM further reduces the factual errors and achieves the lowest NE_{ER} (14.5%) and the highest Entail (25.5%). Surprisingly, our method on 530B LM lead to less diverse generation than 1.3B LM despite the significant improvement in the generation quality (i.e., near perfect repetition scores 0.1% 0.2%). We conjecture that this is the trade-off between the factuality and diversity for 530B LM.

7 Conclusion

In this work, we establish a benchmark to measure and analyze factuality in open-ended text generation tasks. We propose factual-nucleus sampling that improves generation factuality at inference-time, and the combination of sentence completion loss and TOPICPREFIX pre-processing that improves factuality at training-time. We demonstrate that our methods are effective in improving the factuality. Lastly, our results shed light on the existence of the trade-off between diversity and factuality. We strongly believe this is an important insight that will help researchers make a better-informed decision about their model design - i.e., appropriately prioritize the desirable attribute of their LM (factuality vs. diversity) according to the final goal of their task. Potential future work would be to reduce the degree of the observed trade-offs.

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Checklist

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes]
   (b) Did you describe the limitations of your work? [Yes]
   (c) Did you discuss any potential negative societal impacts of your work? [Yes] Our work improves the factual accuracy of large-scale language models and will have positive social impacts.
   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes]
2. If you are including theoretical results...
   (a) Did you state the full set of assumptions of all theoretical results? [N/A]
   (b) Did you include complete proofs of all theoretical results? [N/A]
3. If you ran experiments...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [No]
   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes]
   (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [No]
   (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [Yes] Our experiments are conducted on the DGX A100 servers with 8x A100 GPUs.
4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...
   (a) If your work uses existing assets, did you cite the creators? [N/A]
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   (d) Did you discuss whether and how consent was obtained from people whose data you're using/curating? [N/A]
   (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? [Yes] We only use Wikipedia data that does not contain personally identifiable information or offensive content.
5. If you used crowdsourcing or conducted research with human subjects...
   (a) Did you include the full text of instructions given to participants and screenshots, if applicable? [N/A]
   (b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? [N/A]
   (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [N/A]