Generating Benchmarks for Factuality Evaluation of Language Models

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Abstract

Before deploying a language model (LM) within a given domain, it is important to measure its tendency to generate factually incorrect information in that domain. Existing factual generation evaluation methods focus on facts sampled from the LM itself, and thus do not control the set of evaluated facts and might under-represent rare and unlikely facts. We propose FACTOR: Factual Assessment via Corpus TransfORmation, a scalable approach for evaluating LM factuality. FACTOR automatically transforms a factual corpus of interest into a benchmark evaluating an LM's propensity to generate true facts from the corpus vs. similar but incorrect statements. We use our framework to create two benchmarks: *Wiki-FACTOR* and *News-FACTOR*. We show that: (i) our benchmark scores increase with model size and improve when the LM is augmented with retrieval; (ii) benchmark score correlates with perplexity, but the two metrics do not always agree on model ranking; and (iii) when perplexity and benchmark score disagree, the latter better reflects factuality in open-ended generation, as measured by human annotators. We make our data and code publicly available.[1]

1 Introduction

Despite rapid improvements in their capabilities, large Language Models (LMs) still tend to generate factually inaccurate or erroneous text (Lin et al., 2022; Maynez et al., 2020; Huang et al., 2020). Such phenomena can pose a significant hurdle to deploying LMs in important or sensitive settings, motivating the development of methods for evaluating LM factuality in generation. Previous work evaluates the knowledge stored in LMs by using static sets of facts (Petroni et al., 2019, 2021; Roberts et al., 2020), *e.g.*, via measuring their ability to answer a predefined set of knowledge-intensive questions. Since these facts are tested

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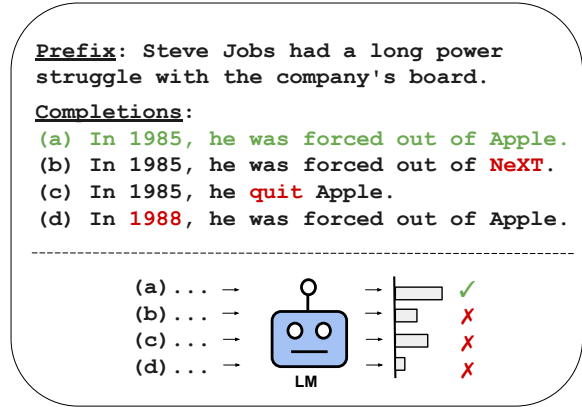[1]https://github.com/AI21Labs/factor

Figure 1: Each example in our evaluation task (dubbed FACTOR) consists of a *prefix* and four *completions*, of which only one is factually correct (completion (a) in this example). The non-factual completions (b), (c) and (d), marked in red, are generated according to different factual error types, detailed in Table 1. The evaluated model assigns likelihood scores to each completion separately. It is considered "correct" if it assigns the highest likelihood to the factually correct completion over all non-factual alternatives.

in isolation and without context, they serve only as a proxy measure of an LM's behavior during open-ended generation.

Alternative methods for directly evaluating an LM's propensity towards factual generations were recently proposed by Lee et al. (2022) and Min et al. (2023). These methods take the straightforward approach of sampling long outputs from a model and applying an automatic pipeline for fact verification, assigning a score corresponding to the percentage of generated facts which are correct. However, the sampling approach may introduce bias: by scoring the accuracy of facts that an LM tends to generate in an open-ended setting, high-likelihood common facts are over-represented, while the "long-tail" of rarer facts is under-represented. This limits our control over which facts are evaluated.

This paper introduces a new and complementary

method for uniformly and inexpensively testing a model's tendency to generate factual information from a given factual corpus: Factual Assessment via Corpus TransfORmation (*FACTOR*). The key idea is automatically perturbing factual statements taken from the corpus to create a constant number of false variations (hereafter, 3) for each true statement (Figure 1). The LM's FACTOR accuracy on our benchmark is defined as the percentage of examples for which it assigns higher likelihood to the factual completion than to any of the false variations. We employed InstructGPT (Ouyang et al., 2022) to generate the false variations for each true statement, according to the FRANK factual error typology (Pagnoni et al., 2021).

We applied FACTOR to Wikipedia and to the news domain, constructing two new, challenging benchmarks that we dub *Wiki-FACTOR* and *News-FACTOR*. We used these datasets to evaluate a large suite of LMs from the OPT (Zhang et al., 2022), GPT-2 (Radford et al., 2019), and GPT-Neo (Black et al., 2021) families, ranging from 110M to 66B parameters. We show in §5.1 that, as expected, FACTOR scores increase with model size. However, even the largest models we evaluated achieved scores of only 58% for Wiki-FACTOR and 68% for News-FACTOR, indicating that these benchmarks are challenging even for large LMs.

We discuss three additional experimental findings. First, in §5.2 we report significant improvements in FACTOR when the LMs are augmented with the simple retrieval component used by Ram et al. (2023). While Ram et al. (2023) demonstrate the gains of their method via the LM perplexity measure, our results directly demonstrate that retrieval augmentation improves factuality in the LM setting. Second, we show that FACTOR accuracy and LM perplexity tend to be highly correlated but sometimes induce different orderings between LMs (see Figure 2). Of course, while perplexity is indeed affected by the likelihood of facts mentioned in the corpus, it is also affected by many additional linguistic phenomena. Third, in §5.3 we report on pairs of models that share similar perplexity but differ significantly in terms of FACTOR accuracy. In §6, we report findings of a manual annotation effort over 1, 200 genrated completions, which reinforces FACTOR accuracy as predictive of factuality in open-ended generation.
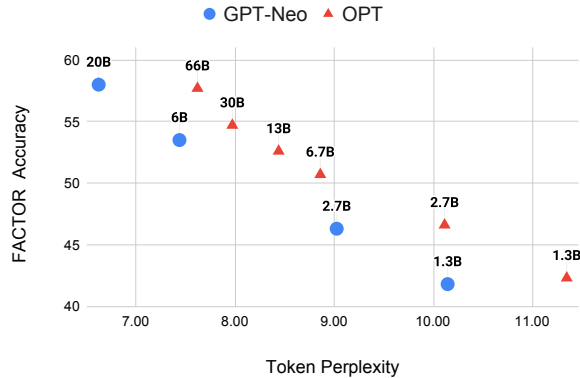

Figure 2: Wiki-FACTOR scores versus LM perplexity on Wikipedia for LMs from the GPT-Neo model family (blue circle, sizes (1.3B-20B)) and the OPT model family (red triangle, 1.3B-66B). Labels indicate sizes (in billions). The two measures correlate but can disagree on ranking, e.g., the OPT-66B LM has higher perplexity but better Wiki-FACTOR accuracy than the GPT-J-6B LM. In §6 we annotate text generated out of both models and show that better Wiki-FACTOR is predictive of more factual text generation.

2 Related Work

Factuality Evaluation for LMs Many well-established benchmarks for evaluating factual knowledge are focused on knowledge-intensive downstream tasks like question answering, fact verification, and slot filling (Petroni et al., 2019, 2021; Roberts et al., 2020; Jiang et al., 2020; Elazar et al., 2021; Mallen et al., 2023). This body of work tests models in a simplified uncontextualized setting, testing knowledge of each fact in isolation. Tam et al. (2023) proposed evaluating LMs' *factual consistency* against a grounding context through summarization. FACTOR extends those benchmarks to a text generation setting, in which the evaluated facts are contextualized.

Recent work by Lee et al. (2022) and Min et al. (2023) propose automatically scoring the factuality of a sample of free-form LM generations on a certain topic. These approaches make it hard to control the facts contributing to the evaluation score, and moreover they are biased towards common facts, since they are generated by the evaluated LM itself.

Contrastive Datasets Contrastive evaluation, in which the model's ability to discern between similar positive and negative examples is tested, is a long-standing approach used in a wide range of tasks (Sennrich, 2017; Burlot and Yvon, 2017; Glockner et al., 2018; Kaushik et al., 2020; Glock-

ner et al., 2018). For factuality evaluation, the contrastive approach is applied by perturbing factual claims to obtain negative examples. Schuster et al. (2021) performed synthetic edits to Wikipedia sentences with crowd workers, while Liu et al. (2022) used BERT (Devlin et al., 2019) to make local replacements, verified by human annotators. Gupta et al. (2022) used model and rule-based heuristics to perturb factual claims in dialogue.

Following recent work, which showed that contemporary large LMs can be instructed to generate high quality evaluation sets (Perez et al., 2023), our FACTOR approach leverages those capabilities to generate contextualized, fluent, diverse and challenging non-factual claims, as described in the following section.

3 The FACTOR Evaluation Approach

This section describes our proposed approach of Factual Assessment via Corpus TransfORmation, or FACTOR. Given an (unlabeled) evaluation corpus, we define a multi-choice task where each example is comprised of a multi-sentence prefix, a single *factual* next sentence completion, and three *non-factual* alternative completions (Figure 1). In §3.1 we present several properties required of a FACTOR benchmark, and describe the error verticals along which we generate non-factual alternatives. We then describe our FACTOR dataset creation pipeline, which given a corpus generates a FACTOR benchmark automatically (§3.2). Lastly, we describe our application of this pipeline to two corpora: Wikipedia and news, creating Wiki-FACTOR and News-FACTOR, and verify the quality of these datasets through manual annotations against the required properties (§3.3).

3.1 The Evaluation Task: *FACTOR*

We now formally describe the FACTOR multi-choice factual evaluation task. Each instance (or example) of our task contains a prefix text t comprised of several sentences, along with four possible full sentence completions, of which only one is factually correct. We choose the original completion (*i.e.*, the continuation of t in the corpus) as the factually correct one. We denote this correct completion as c^+, and the non-factual completions as $\mathcal{C}^- = \{c_1^-, c_2^-, c_3^-\}$. We evaluate models by measuring the percentage of examples for which they assign the highest mean log-probability to c^+. To put formally, the model is correct on a given

example if

$$c^+ = \operatorname*{argmax}_{c \in \{c^+\} \cup \mathcal{C}^-} \frac{\log p(c|t)}{|c|}, \qquad (1)$$

where $|c|$ is the length of completion c in tokens. We refer to the percentage of correct examples as the FACTOR accuracy.

Generally, we require each of the "incorrect" completions $c^- \in \mathcal{C}^-$ to satisfy the following properties:

1. *Non-factual*: c^- contains a false claim;

2. *Fluent*: c^- is grammatical;

3. *Similar to the factual completion*: c^- has a small edit-distance from c^+.

The second and third properties are aimed at making it harder to distinguished between the factual and non-factual completions for reasons other than their factual correctness, such as fluency or style. Furthermore, it is desirable that the non-factual completions be logical and self-consistent, to make them more difficult to eliminate. For example, for $c^+ =$"*They got married in 2010 and divorced in 2017*", then $c^- =$"*They got married in 2010 and divorced in 2019*" is a good non-factual completion since it checks whether the model knows the divorce year, while $c^- =$"*They got married in 2010 and divorced in 2009*" only evaluates the model's knowledge of the temporal relations between marriage and divorce.

Error Types Ideally, non-factual completions in a FACTOR dataset should span a diverse variety of factuality error types. To achieve this, we adopt the error typology introduced in FRANK (Pagnoni et al., 2021) for factual evaluation in summarization. While they introduced their error typology to categorize factual inconsistencies of generated summaries w.r.t. the source document, we instead leverage this typology to vary the type of factual inconsistencies that hold between between our non-factual completions and the prefix and completion (t and c^+). We focus on the five error types from two categories: semantic frame errors and discourse errors (examples shown in Table 1):

- *Predicate* error: a predicate that is inconsistent with c^+ or t.

- *Entity* error: The subject or object of a predicate are inconsistent with c^+ or t.

Original text (completion in bold)	*...In 1982, Donne was appointed as the first Queen's Representative to the Cook Islands.* ***After completing his term, he became Chief Justice of Nauru and Tuvalu in 1985.***
Error Type	**Example**
Entity	*After completing his term, he became the Queen's Representative to the Cook Islands in 1985.*
Predicate	*After completing his term, he declined the position of Chief Justice of Nauru and Tuvalu in 1985.*
Circumstance	*After completing his term, he became Chief Justice of Nauru and Tuvalu in 1987.*
Coreference	*After completing her term, she became Chief Justice of Nauru and Tuvalu in 1985.*
Link	*Before completing his term, he became Chief Justice of Nauru and Tuvalu in 1985.*

Table 1: Error types examples. The original text (top) consists of a prefix and a completion sentence (marked in bold). Each example introduce different perturbation over the original completion of different type (edit marked in red).

- *Circumstance* error: The completion contains information describing the circumstance of a predicate (*e.g.*, location, time, manner) that is inconsistent with c^+ or t.

- *Coreference* error: The contradiction is inconsistent with a pronoun/reference in c^+ or t, referring to a wrong or non-existing entity.

- *Link* error: c^- is inconsistent with c^+ or t in the way that different statements are linked together (causal/temporal links).

3.2 Generating FACTOR Benchmarks

Given an evaluation corpus, we generate a FACTOR benchmark automatically, in a process designed to meet the requirements presented in §3.1. The dataset creation process follows a four-stage pipeline: (1) prefix and completion selection, (2) non-factual completion generation, (3) non-factual completion filtering, and (4) non-factual completion selection.

3.2.1 Prefix and Factual Completion Selection

We select a single sentence from each document as a factually correct completion c^+. We exclude headlines and sentences with fewer than 10 words. The prefix t is set to be the entire text preceding c^+ in the document.

3.2.2 Non-factual Completion Generation

Given a prefix t and its original completion c^+, we use InstructGPT (davinci-003; Ouyang et al. 2022) to generate a set of contradictory completions. We designed a specific prompt instructing the model to generate contradictions corresponding to each type of error. We only apply each prompt to sentences that are relevant to its error type (determined through simple heuristics, see Appendix A.1 for details).

The prompts are designed as follows:

- Multiple contradiction generation: the model is prompted to generate multiple subsequent contradictions in each sampling operation. Therefore, the model creates new completions conditioned on its previous ones. In preliminary experiments, we found this sampling practice to improve diversity when compared to multiple independent sampling of completions.

- Edit planning: for each contradiction, the model first explicitly generates the planned edits over the original completion, and then applies those edits by writing the entire *modified* completion (similar to chain-of-thought prompting; Wei et al. 2022). For example, generating the coreference error in Table 1 is done by first explicitly writing the edits

Property	Wiki	News
Non-factual	97.6	98.3
Fluent	94.0	97.0
Self-Consistent	87.4	87.3
Edit-Distance	2.3±(1.4)	2.1±(1.4)

Table 2: Validation results: (1) percentage of generation that meet each desired property in Wiki-FACTOR (Wiki) and News-FACTOR (News), estimated by manual annotation over sub-samples (top), (2) mean edit-distance between the generations and their original completion (bottom).

(*"Changes: 'his' to 'her', 'he' to 'she' "*), before generating the contradiction. This encourages the model to make minimal edits. See full prompts in the appendix.

Appendix D lists the full prompts that we used for all error types.

3.2.3 Non-factual Completion Filtering

We considered the set of generated completions as candidates for non-factual completions. We applied automatic tools to filter out (i) *non-contradictory* and (ii) *non-fluent* completions.

Non-Contradictory Completions Given a candidate completion c, we asserted that it was indeed contradictory to the original completion c^+ by applying a NLI model.[2] The *premise* was set to be c^+ along with its near context (*i.e.*, the last tokens of the prefix t; denoted by t_{near}). The *hypothesis* was set to be c, also preceded by t_{near}. We selected generations that the NLI model classified as contradictory with a probability higher than a fixed threshold τ_{NLI}, i.e.:

$$p_{NLI}(\text{contradiction} \mid [t_{near}; c^+], [t_{near}; c])) > \tau_{NLI}$$

We chose $\tau_{NLI} = 0.6$ (except for contradictions generated by the coreference error prompt, where we set $\tau_{NLI} = 0.3$) after using a manual validation process detailed Appendix A.2.

Non-Fluent Completions To verify that c is a fluent completion we used GPT2-Small (Radford et al., 2019) scores, similar to Gupta et al.

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[2]We used DeBERTa-large model (He et al., 2021) fine-tuned on the MNLI dataset (Williams et al., 2018) from Hugging Face: microsoft/deberta-large-mnli.

Type	Wiki	News
Predicate	25.4	31.3
Entity	42.8	48.0
Circumstance	24.2	16.0
Coreference	4.4	2.3
Link	3.2	2.3

Table 3: Annotated error type distribution for Wiki-FACTOR (Wiki), and News-FACTOR (News).

(2022): We filtered out generations with mean log-likelihood lower than the original completion's by a fixed margin τ_{LM}. Formally, we selected a completion c if it satisfied:

$$\frac{\log p(c|t)}{|c|} > \frac{\log p(c^+|t)}{|c^+|} - \tau_{LM}$$

Using a manual validation detailed in Appendix A.2, we set $\tau_{LM} = 0.2$.

3.2.4 Non-factual Completion Selection

Finally, we selected the non-factual completions c_1^-, c_2^-, c_3^- from the candidates that passed the filtering phase. In order to increase diversity in error types, we first selected a single completion from each type. In cases where fewer than three generations overall met the criteria from §3.2.3, we added completions from already used error types.

3.3 Applying FACTOR to Wikipedia and News Domains

We focused on two knowledge intensive domains: Wikipedia (encyclopedic knowledge) and news (current events). We constructed two evaluation datasets following the above described procedure:

- *Wiki-FACTOR:* a dataset based on the Wikipedia section of The Pile's validation split (Gao et al., 2021), containing 2994 examples.

- *News-FACTOR:* a dataset based on Reuters articles published after 1/10/2021, extracted from The RefinedWeb Dataset (Penedo et al., 2023). The dataset consists of 1036 examples.

3.3.1 Dataset Validation

To validate that Wiki-FACTOR and News-FACTOR meet the required FACTOR properties detailed in §3.1, we manually evaluated a sub-sample from each dataset. We sampled 138 examples from Wiki-FACTOR and 100 examples from

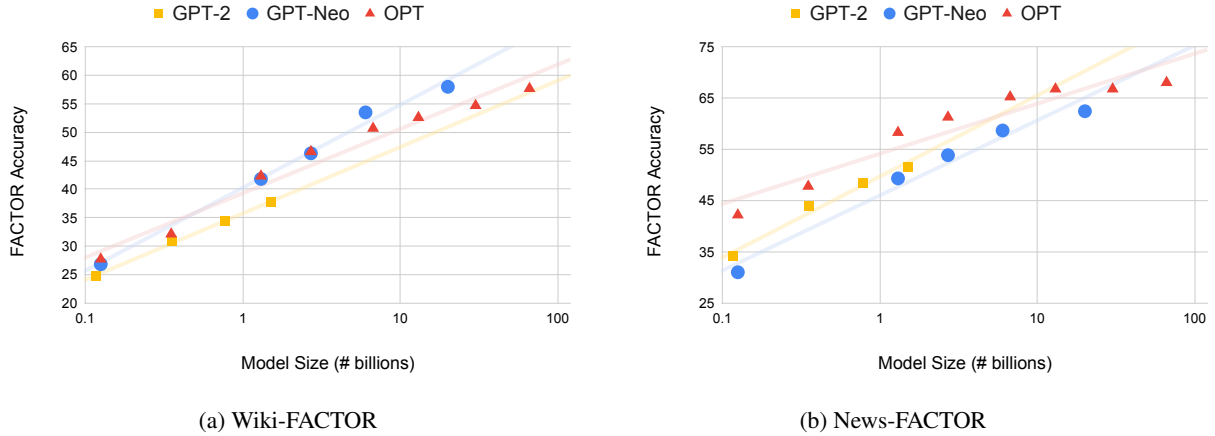(a) Wiki-FACTOR   (b) News-FACTOR

Figure 3: Accuracy per model size for Wiki-FACTOR (left) and News-FACTOR (right), for models from GPT-2 (blue circle), GPT-Neo (red triangle), and OPT (yellow square) families.

News-FACTOR, containing 414 and 300 generations overall. Each generation was annotated w.r.t. the properties manifested in §3.1, namely whether they were (1) non-factual, (2) fluent, and (3) self-consistent. To assess the dataset diversity, we annotated the contradictions in accordance with the error typology of Pagnoni et al. (2021), described in §3.1. In addition, we verified that the non-factual completions were similar to the factual completion by measuring their mean edit distances over all the examples.

Table 2 shows the validation results. For both datasets, almost every generated completion indeed contradicted the corresponding original completion, was fluent, and was self consistent. Table 3 shows the error type distribution. For both datasets we observed that FACTOR yielded diverse contradiction types. Semantic frame errors (Entity, Predicate, and Circumstance) were more prevalent than discourse errors (Link and Coreference), as more sentences are suited for these type of errors.

4 Experimental Setup

We use *Wiki-FACTOR* and *News-FACTOR* (§3.2) to evaluate factual knowledge of various LLMs from different model families. In addition, we explore how grounding on an external corpus can affect factual knowledge. Specifically, we leveraged an existing Wikipedia retrieval-corpus to evaluate retrieval augmented models over Wiki-FACTOR. We further investigate our FACTOR approach, compare it to perplexity, and examine how its links to factuality in generation (§6).

4.1 Datasets

The Wiki-FACTOR and News-FACTOR datasets are described in §3.3. For perplexity evaluation (§5.3) , we selected a subset of 300 Wikipedia articles from the documents Wiki-FACTOR is based on, containing approximately 367K tokens.

4.2 Models

We performed our experiments over a set of open source models. We evaluated four models of GPT-2 family (110M–1.5B parameters; Radford et al. 2019), five models from the GPT-Neo family (125M–20B; Black et al. 2021, 2022; Wang and Komatsuzaki 2021), and eight models of OPT (125M–66B; Zhang et al. 2022). We capped the sequence length at 1024 tokens, so all models could be directly compared to each other.

The corpora that Wiki-FACTOR and News-FACTOR were constructed from were not used for training any of the examined models. News-FACTOR is based on articles published after 1/10/2021, beyond the models' data cutoff date. Wiki-FACTOR is based on Wikipedia documents from The Pile's validation split, which is not part in any of the models' training sets (OPT and GPT-Neo models were trained on The Pile's training split, GPT-2 models were not trained on Wikipedia).

4.3 Retrieval-Augmented Models

In §5.2, we present evaluations of retrieval-augmented variants of the models. To that end, we adopted the In-Context RALM (IC-RALM) framework of Ram et al. (2023), where the retrieved document is prepended to the LLM's input, without any further training or specialized LLM architec-
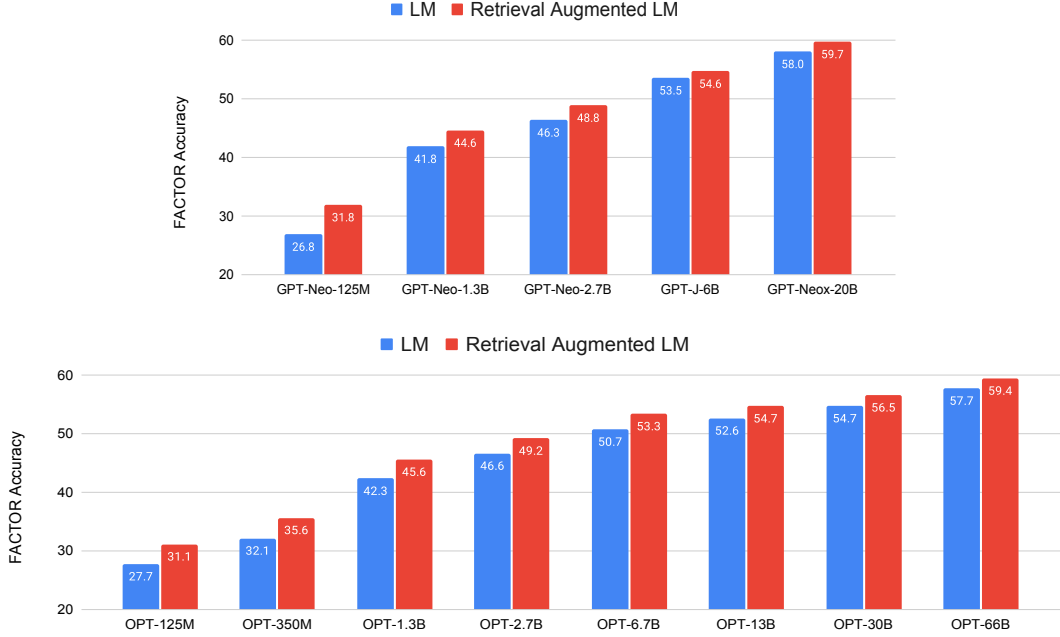
Figure 4: Factual accuracy over Wiki-FACTOR for GPT-Neo and OPT models, compared to their IC-RALM variants. IC-RALM leads to consistent improvement for all models.

ture. In IC-RALM, a retriever is called every s tokens (*i.e.*, the retrieval *stride*), with a query comprised of the last ℓ tokens. The top-scored retrieved document is then prepended to the LLM's input. The LLM is run with the concatenated input to assign log-probabilities to the next s tokens.

Similar to Ram et al. (2023), we used the lexical BM25 (Robertson and Zaragoza, 2009) over the Wikipedia corpus,[3] excluding the evaluated docs. We set $s = 8$ and $\ell = 32$.

5   Factual Knowledge Evaluation Results

This section describes the experimental evaluation of LLM factuality with Wiki-FACTOR and News-FACTOR. In §5.1 we show that FACTOR accuracy increases with LM size but also depends on the training data (different model families differ in scores). In §5.2 we show that retrieval augmentation of the LM improves FACTOR accuracy, positioning FACTOR accuracy as a first automatic measure of factuality improvement for retrieval augmented LM methods. Finally, in §5.3 we show that while corpus perplexity and FACTOR accuracy correlate, their pairwise model ranking can significantly differ. This outcome, along with manual validation of the correlation between FACTOR accuracy and factual generation in §6, solidifies

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[3]We used the Wikipedia corpus of Karpukhin et al. (2020), based on the dump from Dec. 20, 2018.

FACTOR accuracy as a novel automatic measure for evaluating the proneness of an LM to generate factual information in a certain domain.

5.1   Factual Knowledge Improves with Model Size

We evaluate models from the GPT-2, GPT-Neo, and OPT families on LLMs with Wiki-FACTOR and News-FACTOR. Results are presented in Figure 3. As expected, within a specific model family, larger models generally outperform smaller ones.

However, even the largest models are capped at 58.0% (GPT-NeoX-20B) and 68.1% (OPT-66B) on Wiki-FACTOR and News-FACTOR respectively, indicating that these benchmarks are challanging.

We observe that all models achieve higher FACTOR accuracy on news than Wikipedia when comparing the two domains. We hypothesize that since news articles tend to cover more specific events, the prefix may be more useful for detecting the factual completions. In addition, when comparing between different model-families, we find that the OPT models leads on News-FACTOR, while the GPT-Neo family leads on Wiki-FACTOR. This implies that the different data sources used for training these two model families are suited to different domains.

5.2 The Effect of Retrieval Augmentation on Factual Knowledge

Next, we ask: *Can FACTOR accuracy be improved by augmenting models with a retrieval component?* Importantly, while a clear motivation for retrieval augmentation is factual grounding of the LM, no existing metrics allow direct measurement of the factuality enhancement over a corpus in a retrieval augmented LMs. The imperfect measure of LM perplexity in often used to assess these methods (Khandelwal et al., 2020; Borgeaud et al., 2022; Ram et al., 2023; Shi et al., 2023), and we propose FACTOR accuracy as a more direct measure of factuality.

To explore this question, we compared the accuracy of LLMs to that of their retrieval-augmented counterparts, implemented following the IC-RALM framework (§4.3; Ram et al. 2023). Figure 4 compares the FACTOR accuracy of models in GPT-Neo and OPT families against their IC-RALM variants over Wiki-FACTOR. We observed consistent gains from augmenting the models with retrieval. These results highlight that grounding the model in an external corpus can improve its factual predictions. Since the retriever used in our experiments is used in an "off-the-shelf" manner, we speculate that further performance boosts may be gained by a retriever or reranker specialized for this task (Izacard et al., 2022; Ram et al., 2023).

Another interesting finding is that the *relative* gains in FACTOR accuracy obtained by IC-RALM, are more moderate compared to the relative gains in perplexity over WikiText-103 (Merity et al., 2016), reported by Ram et al. (2023). In the next section we further explore the connection between perplexity and FACTOR accuracy.

5.3 Perplexity Correlates but is not Always Aligned with FACTOR Accuracy

We investigate whether FACTOR evaluation adds additional information beyond perplexity, when used as a comparative metric for selecting which LM to use within a certain corpus. Figure 2 shows the FACTOR accuracy of models on Wiki-FACTOR, compared to their token-level perplexity on the Wikipedia section of The Pile's validation set (§4.1) (Appendix C includes all evaluated models). Overall, we observe a high correlation between the two metrics. However, there are cases where they disagree (*i.e.*, a pair of models where one is better when measured by perplexity

but worse in terms of FACTOR accuracy). For example, GPT-Neo-2.7B is significantly better than OPT-2.7B in terms of perplexity (9.0 vs. 10.1), but slightly worse in terms of FACTOR accuracy (46.3% vs. 46.6%). In addition, GPT-J-6B has lower perplexity compared to OPT-66B (7.4 vs. 7.6), while OPT-66B is significantly better in terms of FACTOR accuracy (57.7% vs. 53.5%). This finding suggests that (i) FACTOR accuracy offers a complementary view of models' performance, not necessarily captured by the standard perplexity metric, and (ii) improvements in perplexity do not necessarily imply better factuality.

6 Factuality in Open-Ended Generation

This section explores the connection between FACTOR accuracy and factuality in open-ended generation, via an experiment based on human annotations.

6.1 Experimental Setup

We considered pairs of prefix, original completion and non-factual completion (t, c^+, c^-) from Wiki-FACTOR. We then manually identified the *minimal factual claim* modified by c^-. For the example given in Table 1, replacing "*became*" with "*declined the position of*" relates to the minimal fact "*Donne became Chief Justice of Nauru and Tuvalu*". We denote the minimal fact by f.

Also, let c be the common prefix of c^+ and c^-. For the example given in Table 1, along with the above replacement of c^+ with c^-, the common prefix c is: "*After completing his term, he*". We let LLMs generate free text, conditioned on the concatenation of t and c. In other words, the model was conditioned on the prefix and the text of the completion until the edit induced by c^-. Note that in this open-ended generative setting the LM might generate the correct fact, text violating it, or any other fluent continuation that does not refer to the specific fact. For each example we manually annotated whether the generated text is *true*, *false*, or *neutral* w.r.t. f.

We analyzed two models with a similar token-level perplexity but a significant gap in FACTOR accuracy: GPT-J 6B and OPT-66B (marked in a green circle in Figure 2).

For each model, we considered two groups of examples: examples with c^+, c^- pairs for which the model was *right*, *i.e.*, c^+, c^- pairs for which:

Model	Subset	Fact. Accuracy
GPT-J 6B	Right	30.0%
	Wrong	10.5%
	All (Weighted)	24.8%
OPT-66B	Right	46.6%
	Wrong	4.6%
	All (Weighted)	**38.8**%

Table 4: Manual factuality annotation results for OPT-66B and GPT-J 6B. For each model, we present the results per *right* and *wrong* subsets. Bottom row shows the weighted average between the *right* and *wrong* variants w.r.t to the *right/wrong* pairs of Wiki-FACTOR.

$$\frac{\log p(c^+|t)}{|c^+|} > \frac{\log p(c^-|t)}{|c^-|}, \qquad (2)$$

and c^+, c^- pairs for which the model was *wrong* (*i.e* the complement of Eq. 2).

We sampled three generations per example for 100 examples from each group and for each model. Overall, we created $2 \times 2 \times 100 \times 3 = 1200$ generations.

We filtered some of the samples due to either ill-formatted generations, non-factual original completions or non-contradictory completions (overall we removed 14.5% of the samples).

6.2 Results

We assess each model's knowledge of the minimal facts for each example through manual annotation. To this end, we only considered generations that are relevant to their minimal fact f, excluding "neutral" generations (which constituted 59.5% and 54.3% for GPT-J 6B and OPT-66B, respectively). For each model, we measure the percentage of generated texts that are true w.r.t. f per the *right* and *wrong* subsets separately. We obtained the overall FACTOR accuracy by weighting between the subsets results according to their distribution in Wiki-FACTOR. Table 4 shows the results of our manual annotation process (full results are given in App. B)

Accuracy over Wiki-FACTOR is linked with factuality in open-ended generation. We found that for examples where models were *wrong*, they also tended to generate significantly more false claims w.r.t their minimal fact. For example, OPT-66B generated a true claim only 4.6% of the times for examples it got wrong, compered to 46.6% for examples for which it was right. This suggests

that the overall performance over FACTOR can shed light on the model's ability to generate factual claims accurately in open-ended generation.

As a comparative metric, accuracy over Wiki-FACTOR aligns with factuality in open-ended generation. We observed significant gaps in manual factuality annotation between OPT-66B and GPT-J 6B: OPT-66B generated *true* claims 38.8% of the time, compared to 24.8% generated by GPT-J 6B. This aligns with the models' performance over Wiki-FACTOR, despite the fact that the two models share roughly the same perplexity on Wiki.

This finding suggests that FACTOR can serve as a better proxy than perplexity when measuring the factuality of a model on a given domain.

7 Discussion

This paper introduced FACTOR, a new approach for quantitatively evaluating LM factuality. FACTOR creates an evaluation benchmark from a given corpus, consisting of contextualized, factual statements from the corpus along with non-factual variations. The LM's FACTOR score describes its tendency to assign greater likelihood to the original fact than to any of the non-factual alternatives. By directly comparing the LM likelihood of factual claims with their non-factual variants, FACTOR correlates with the LM's propensity to generate factual information.

While the approach of generating text and checking for its factuality (Lee et al., 2022; Min et al., 2023) evaluates a model's likeliest behavior, our approach is oriented towards assessing a model's factual grasp of a broader set of facts regardless of their respective likelihoods. We see these two approaches as complementary; together, they can be used to yield a more holistic assessment of LM factuality.

These two methods also differ in terms of costs. The expensive step in FACTOR evaluation is the automatic benchmark creation pipeline for a given corpus, described in §3.2. Once a FACTOR benchmark is created, it is very cheap to evaluate different LMs (or different retrieval augmentation methods, etc) on it. On the other hand, methods that directly evaluate LM generated text must reapply their automatic fact verification pipeline for every generation of every evaluated LM, so they incur a constant high cost for every evaluation. FACTOR allows for a controlled uniform examination of facts within a corpus. Overall, this paper establishes FACTOR as

an scalable and effective approach for assessing an LM's propensity for generating factual text.

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A Technical Details of FACTOR Data Pipeline

A.1 Identifying Sentences' Relevant Error Types

For each sentence, we identify the types of edits we can apply to it. First, we use a part-of-speech tagger to detect relevance for entity error (detecting nouns), predicate error (detecting verbs) and coreference error (detecting pronouns). For circumstances errors, we use Named-Entity Recognition taggers to identify sentences containing locations, dates, and time entities. Finally, we search for temporal/causal link words from a predefined set of words, which implies relevance for link errors.

A.2 Setting Filters Thresholds

As discussed in §3.2.3, we applied two filters to ensure the quality of the potential completions–an NLI filter (to filter out non-contradictory completions) and an LM filter (to filter out non-fluent completions). To choose the thresholds τ_{NLI} and τ_{LM}, we manually annotated 40 samples w.r.t to the properties specified in §3.1 (*i.e.*, (1) contradictory and (2) fluent and self-consistent). We have tested thresholds 0.1-0.9, and chose the threshold which achieved highest precision without filtering out too many samples (max 35% of the samples). For the NLI filter we used DeBERTa-largs model fine-tuned on the MNLI dataset. Best threshold was $\tau_{\text{NLI}} = 0.6$, with precision of 0.96. Manually evaluating the different contradiction types we have noticed this threshold was too harsh for corefrence contradiction (87.5% of the completions were filtered out. Therefore we reduced its threshold to 0.3 which filtered out 75% of the samples). For the LM filter we used GPT2-Small. Best threshold was $\tau_{\text{LM}} = 0.2$, with precision of 0.78.

B Factuality in Open-ended Generation: Extended Results

Table 5 shows the extended results for the manual factuality annotation for open-ended generation experiment §6. In addition to the overall results, we include the distribution of Neutral/True/False annotations. Notably, most generations are neutral for both models. This highlights the limitation of sampled-based approach for assessing model's factual knowledge.
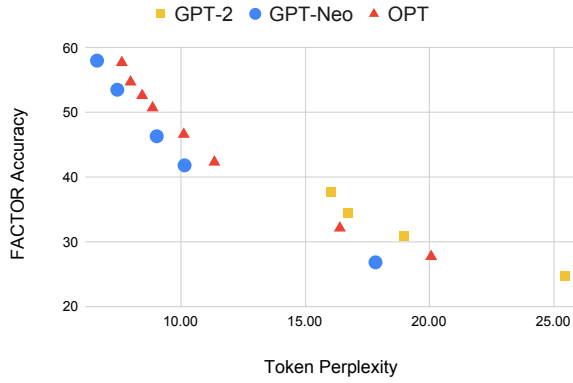
Figure 5: Accuracy per token perplexity over Wiki-FACTOR.

C Comparison between Perplexity and FACTOR Accuracy over Wikipedia

Figure 5 presents Wiki-FACTOR scores versus LM perplexity on Wikipedia. The figure extends Figure 2, presenting all evaluated LMs: models from the GPT-Neo family (blue circle), OPT family (red triangle) and GPT2 family (yellow square).

D Prompts for Contradictions Generation

We prompted the model to generate multiple candidate completions, For each of the five error types: entity (Table 6), circumstance (Table 7), coreference (Table 8), predicate (Table 9 and 10) and link (Table 11). The prompts are concatenated to a given a completion and its near context, with the exception of link-prompt where only the completion is given (we found that the instruct model tends to repeat the context when it's appended to this particular prompt). The prompts instruct the model to first plan its local edits, and then generate the contradiction.

Model	Variant	Neutral	True (T)	False (F)	Fact. Accuracy $\left(= \frac{T}{T+F}\right)$
GPT-J 6B	Right	62.4%	11.3%	26.3%	30.0%
	Wrong	48.8%	5.4%	45.8%	10.5%
	All (Weighted)	59.5%	10.0%	30.5%	24.8%
OPT-66B	Right	54.1%	21.4%	24.5%	46.6%
	Wrong	55.1%	2.1%	42.8%	4.6%
	All (Weighted)	54.3%	17.7%	28.4%	38.8%

Table 5: Manual factuality annotation results for OPT-66B and GPT-J 6B. For each model, we present the results per *right* and *wrong* subsets. Bottom row shows the weighted average between the *right* and *wrong* variants w.r.t to the *right/wrong* pairs of Wiki-FACTOR.

Type	Prompt
Entity	Given a context and a completion, write diverse alternative completions that contradict the original completion meaning.
	First, identify if the completion contains an entity. Then, write the contradiction by modifying an entity or it's property, add additional modifications if necessary.
	Make sure the changes you make are minimal (so only change necessary details to make the sentence plausible). Do not modify dates or quantities.
	##
	Context: "Sorry" is a song by American singer Madonna from her tenth studio album Confessions on a Dance Floor (2005). It was written and produced by Madonna and Stuart Price, and released as the second single from the album on February 7, 2006. It later appeared on Celebration, her 2009 greatest hits album. An uptempo dance song, " Sorry " was one of the first tracks developed for the album and had numerous remix treatments before the ultimate version of the track was finalized.
	Completion: One of the remixes was done by the known band the Pet Shop Boys, featuring added lyrics by the band.
	1. Change: "Pet Shop Boys" to "Maddona".
	Contradiction: One of the remixes was done by the known singer Maddona, featuring added lyrics by the singer. 2. Change: "Pet Shop Boys" to "Depeche Mode".
	Contradiction: One of the remixes was done by the known band Depeche Mode, featuring added lyrics by the band.
	3. Change: "known" to "unfamiliar".
	Contradiction: One of the remixes was done by the unfamiliar band Pet Shop Boys, featuring added lyrics by the band.
	4. Change: "Pet Shop Boys" to "the Killers".
	Contradiction: One of the remixes was done by the known band the Killers, featuring added lyrics by the band.
	##
	Context: {context}
	Completion: {completion}

Table 6: Prompt for entity-errors generation

Type	Prompt
Circumstance	Given a context and a completion, write diverse alternative completions that contradict the original completion meaning. First, identify if the completion describes the circumstances of an event (location or time). If circumstances are mentioned, modify it to contradict the completion. Do not add time or location if they didn't appear in the original completion. Make sure the changes you make are minimal. ## Context: The kingdom had been in long gradual decline since the early 13th century. Had Pagan possessed a stronger central government, the collapse could have been temporary, and the country "could have risen again". But the dynasty could not recover, and because the Mongols refused to fill the power vacuum, no viable center emerged in the immediate aftermath. As a result, several minor states fought it out for supremacy for the better part of the 14th century. Completion: It was only in the late 14th century that two relatively strong powers emerged in the Irrawaddy basin, restoring some semblance of normalcy. 1. Change: "14th" to "15th". Contradiction: It was only in the late 15th century that two relatively strong powers emerged in the Irrawaddy basin, restoring some semblance of normalcy. 2. Change: "Irrawaddy" to "Chindwin". Contradiction: It was only in the late 14th century that two relatively strong powers emerged in the Chindwin basin, restoring some semblance of normalcy. 3. Change: "late" to "mid". Contradiction: It was only in the mid 14th century that two relatively strong powers emerged in the Irrawaddy basin, restoring some semblance of normalcy. ## Context: {context} Completion: {completion}

Table 7: Prompt for circumstance-errors generation

Type	Prompt
Coreference	Given a context and a completion, write diverse alternative completions that contradict the original completion meaning. First, decide if the completion contains a pronoun (such as: he, she, it, they, his, her, its, theirs...) and write the entity it refers to. Write the contradiction by modifying the pronoun to contradict the original coreference. ## Context: His stance in favor of prohibition cost him the votes of four legislators in his own party and the seat went to Republican William O. Bradley. Six years later Beckham secured the seat by popular election, but he lost his re-election bid largely because of his pro-temperance views and his opposition to women's suffrage. Completion: Though he continued to play an active role in state politics for another two decades, he never returned to elected office, failing in his gubernatorial bid in 1927 and his senatorial campaign in 1936. 1. Pronoun: he Change: "he" to "Bradley". Contradiction: Though Bradley continued to play an active role in state politics for another two decades, he never returned to elected office, failing in his gubernatorial bid in 1927 and his senatorial campaign in 1936. 2. Pronoun: he Change: "he" to "Bradley". Contradiction: Though he continued to play an active role in state politics for another two decades, Bradley never returned to elected office, failing in his gubernatorial bid in 1927 and his senatorial campaign in 1936. 3. Pronoun: his Change: "his" to "Bradley's". Contradiction: Though he continued to play an active role in state politics for another two decades, he never returned to elected office, failing in Bradley's gubernatorial bid in 1927 and his senatorial campaign in 1936. ## Context: The early 6th century saw another queen ruling the city, known only as the "Lady of Tikal", who was very likely a daughter of Chak Tok Ich 'aak II. Completion: She seems never to have ruled in her own right, rather being partnered with other rulers. 1. Pronoun: She Change: "She" to "He" and "her" to "his". Contradiction: He seems never to have ruled in his own right, rather being partnered with other rulers. 2. Pronoun: She Change: "She" to "The king" and "her" to "his". Contradiction: The king seems never to have ruled in his own right, rather being partnered with other rulers. 3. Pronoun: She Change: "She" to "Chak Tok Ich". Contradiction: Chak Tok Ich seems never to have ruled in her own right, rather being partnered with other rulers. ## Context: {context} Completion: {completion}

Table 8: Prompt for coreference-errors generation

Type	Prompt
Predicate	Given a context and a completion, write diverse alternative completions, that contradict the original completion meaning by modifying verbs. First, Identify a verb in the original completion, and then write the contradiction by modifying it. Make sure the contradictions are grammatically correct, fluent and consistent. Make any necessary additional modifications to ensure that. ## Context: Homarus gammarus is a large crustacean, with a body length up to 60 centimetres (24 in) and weighing up to 5 – 6 kilograms (11 – 13 lb), although the lobsters caught in lobster pots are usually 23 – 38 cm (9 – 15 in) long and weigh 0.7 – 2.2 kg (1.5 – 4.9 lb). Completion: Like other crustaceans, lobsters have a hard exoskeleton which they must shed in order to grow, in a process called ecdysis (moulting). 1. Change: "shed" to "retain". Additional changes: "in order to grow" to "in order to survive". Contradiction: Like other crustaceans, lobsters have a hard exoskeleton which they must retain in order to survive, in a process called ecdysis (moulting). 2. Change: "grow" to "maintain their size". Contradiction: Like other crustaceans, lobsters have a hard exoskeleton which they must shed in order to maintain their size, in a process called ecdysis (moulting). 3. Change: "shed" to "keep". Additional changes: "in order to grow" to "in order to strengthen". Contradiction: Like other crustaceans, lobsters have a hard exoskeleton which they must keep in order to strengthen, in a process called ecdysis (moulting). ## Context: The ridge offered a natural avenue of approach to the airfield, commanded the surrounding area and was almost undefended. Edson and Thomas tried to persuade Vandegrift to move forces to defend the ridge, but Vandegrift refused, believing that the Japanese were more likely to attack along the coast. Completion: Finally, Thomas convinced Vandegrift that the ridge was a good location for Edson's Raiders to rest from their actions of the preceding month. 1. Change: "rest" to "keep up". Contradiction: Finally, Thomas convinced Vandegrift that the ridge was a good location for Edson's Raiders to keep up with their actions of the preceding month. 2. Change: "convinced Vandegrift" to "made Vandegrift doubt". Contradiction: Finally, Thomas made Vandegrift doubt that the ridge was a good location for Edson's Raiders to rest from their actions of the preceding month. 3. Change: "rest" to "continue". Contradiction: Finally, Thomas convinced Vandegrift that the ridge was a good location for Edson's Raiders to continue their actions of the preceding month. ## Context: According to a report titled Wolves in Sheep's Clothing, which documents the increase in potentially violent, profane, and sexual content in children's programming, the Parents Television Council, a watchdog media group, and fans believed the SpongeBob SquarePants episode" Sailor Mouth "was an implicit attempt to promote and satirize use of profanity among children. Completion: The episode originally aired during the 2001 – 02 television season, ironically the season in which the PTC named SpongeBob SquarePants among the best programs on cable television, but the report cited a repeat broadcast of the episode from 2005 to prove its point that it promoted use of profanity among children. 1. Change: "prove" to "refute". Additional changes: "best" to "most profane". Contradiction: The episode originally aired during the 2001 – 02 television season, ironically the season in which the PTC named SpongeBob SquarePants among the most profane programs on cable television, but the report cited a repeat broadcast of the episode from 2005 to refute its point that it promoted use of profanity among children. 2. Change: "originally aired" to "pulled off". Contradiction: The episode was pulled off from the 2001 – 02 television season, ironically the season in which the PTC named SpongeBob SquarePants among the best programs on cable television, but the report cited a repeat broadcast of the episode from 2005 to prove its point that it promoted use of profanity among children. ## Context: {context} Completion: {completion}

Table 9: Prompt for predicate-errors generation (the rest of the prompt is in table 10)

Type	Prompt
Predicate	Context: By Part II of the series, Shikamaru is capable of utilizing multiple shadow-based techniques at once and can lift his shadow from the ground in order to interact with physical objects; for instance, he can pierce enemies with the shadow tendrils or use them to throw weapons. Shikamaru approaches the exams with a sense of apathy; when he battles the Sunagakure ninja Temari, he defeats her but forfeits his match to her, due to his chakra being low. Completion: Despite this loss, he is the only ninja among his peers to be promoted to the rank of Chunin, as the overseers of the exams were impressed by the insight and intelligence he demonstrated against Temari. 1. Change: "promoted" to "demoted". Additional changes: "Despite" to "Due", "as" to "although". Contradiction: Due to this loss, he is the only ninja among his peers to be demoted to the rank of Chunin, although the overseers of the exams were impressed by the insight and intelligence he demonstrated against Temari. 2. Change: "were impressed" to "underappreciated". Additional changes: "as" to "although". Contradiction: Despite this loss, he is the only ninja among his peers to be promoted to the rank of Chunin, although the overseers of the exams underappreciated the insight and intelligence he demonstrated against Temari. 3. Change: "demonstrated" to "failed to demonstrate". Additional changes: "as" to "although", "impressed" to "disappointed". Contradiction: Despite this loss, he is the only ninja among his peers to be promoted to the rank of Chunin, although the overseers of the exams were disappointed by the insight and intelligence he failed to demonstrate against Temari. ## Context: {context} Completion: {completion}

Table 10: Prompt for predicate-errors generation (continue of the prompt in table 9)

Type	Prompt
Link	Given a sentence, write contradictory sentences by modifying a temporal link. First, identify a link between events, and then modify it. Make sure the contradictions are grammatically correct and fluent. If no such link exists, answer "NA". ## Sentence: Prior to filming, a week was spent reinforcing the roof of the liquor store to ensure it would not collapse if it were to be intruded by a group of fans. 1. Change: "prior to" to "after". Contradiction: After filming, a week was spent reinforcing the roof of the liquor store to ensure it would not collapse if it were to be intruded by a group of fans. ## Sentence: Lewis McAllister, a businessman in Tuscaloosa, Alabama, was the first Republican to serve in the Mississippi House of Representatives since Reconstruction, 1962-1968; he resided in Meridian prior to 1971. 1. Change: "prior to" to "after". Contradiction: Lewis McAllister, a businessman in Tuscaloosa, Alabama, was the first Republican to serve in the Mississippi House of Representatives since Reconstruction, 1962-1968; he resided in Meridian after 1971. 2. Change: "since" to "before" Contradiction: Lewis McAllister, a businessman in Tuscaloosa, Alabama, was the first Republican to serve in the Mississippi House of Representatives before Reconstruction, 1962-1968; he resided in Meridian prior to 1971. ## Sentence: The decline of the railroad industry caused significant job losses, resulting in a population decline as workers left for other areas. 1. Change: "caused" to "caused by". Contradiction: The decline of the railroad industry, caused by significant job losses, resulting a population decline as workers left for other areas. 2. Change: "resulting" to "was the result of". Contradiction: The decline of the railroad industry caused significant job losses, was the result of a population decline, as workers left for other areas. ## Sentence: {completion}

Table 11: Prompt for link-errors generation