FACTSCORE: Fine-grained Atomic Evaluation of Factual Precision in Long Form Text Generation

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Abstract

Evaluating the factuality of long-form text generated by large language models (LMs) is non-trivial because (1) generations often contain a mixture of supported and unsupported pieces of information, making binary judgments of quality inadequate, and (2) human evaluation is time-consuming and costly. In this paper, we introduce **FACTSCORE**, a new evaluation that breaks a generation into a series of atomic facts and computes the percentage of atomic facts supported by a reliable knowledge source. We conduct an extensive human evaluation to obtain FACTSCOREs of people biographies generated by several state-of-the-art commercial LMs—InstructGPT, ChatGPT, and the retrieval-augmented PerplexityAI—and report new analysis demonstrating the need for such a fine-grained score (e.g., ChatGPT only achieves 58%). Since human evaluation is costly, we also introduce an automated model that estimates FACTSCORE using retrieval and a strong language model, with less than a 2% error rate. Finally, we use this automated metric to evaluate 6,500 generations from a new set of 13 recent LMs that would have cost $26K if evaluated by humans, with various findings: GPT-4 and ChatGPT are more factual than public models, and Vicuna and Alpaca are some of the best public models. We will open source FACTSCORE as a Python package.

1 Introduction

Long-form text generated by large language models (LMs) has widely been used (Brown et al., 2020; Ouyang et al., 2022); nonetheless, evaluating their *factual precision*—whether each piece of information conveyed in a generation is factually accurate—remains challenging for two reasons. First, a generation consists of a large number of pieces of information that are a mixture of true or false,[1] making a binary judgment inadequate (Pagnoni et al., 2021). Second, validating every piece of information is time-consuming and costly.

In this paper, we introduce **FACTSCORE** (**F**actual precision in **Atomicity** **Score**), a new evaluation of an LM that represents *the percentage of atomic facts (pieces of information) supported by a given knowledge source*. Computing FACTSCORE involves (1) breaking a generation into a series of atomic facts—short statements that each contain one piece of information (Nenkova and Passonneau, 2004; Shapira et al., 2019; Zhang and Bansal, 2021; Liu et al., 2022), and (2) assigning a binary label to each atomic fact, allowing a fine-grained evaluation of factual precision. We evaluate FACTSCORE

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[1] Even a single sentence consists of multiple pieces of information (e.g., 4.4 per sentence in ChatGPT, 40% of which are a mixture of supported and unsupported information).

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on the task of generating people biographies because generations consist of verifiable statements rather than debatable or subjective ones, and the scope is broad (i.e., covering diverse nationalities, professions, and levels of rarity).

We perform extensive human annotations to obtain FACTSCOREs of three state-of-the-art, commercially available LMs: InstructGPT (Ouyang et al., 2022), ChatGPT (OpenAI, 2022), and search-augmented PerplexityAI.[2] Our results indicate that commercially available LMs are riddled with errors, having FACTSCOREs of 42%, 58% and 71%, respectively. Their FACTSCOREs significantly drop as the rarity of the entities increases, e.g., 80% → 16% for ChatGPT.

Since human evaluation is costly, we next introduce an automatic evaluation of FACTSCORE through a model that estimates a FACTSCORE for a given LM. Our estimator decomposes generations into atomic facts and validates each based on a given knowledge source, leveraging retrieval from the given knowledge source and strong language models. Our estimator closely approximates FACTSCORE with an error rate of $< 2\%$ and can be applied to a range of *new* LMs at scale with no human effort. Our case study evaluates 6,500 generations from 13 LMs that could have cost $26K, with various findings: GPT-4 (OpenAI, 2023) and ChatGPT are far less factual than humans but are much better than public models, and there is a large variance between public models, with Vicuna (Chiang et al., 2023) and Alpaca (Taori et al., 2023) being some of the best.

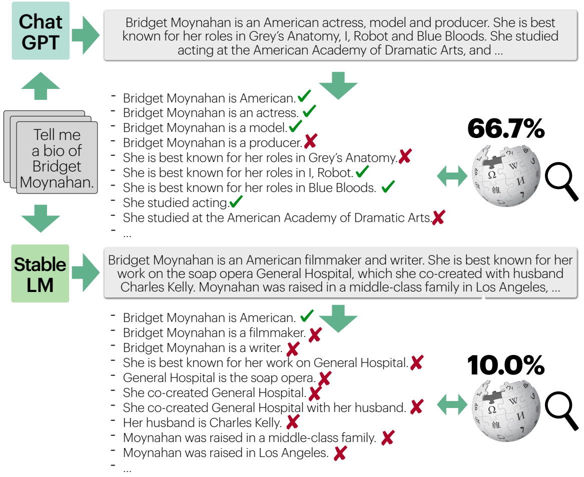
Chat GPT
Bridget Moynahan is an American actress, model and producer. She is best known for her roles in Grey's Anatomy, I, Robot and Blue Bloods. She studied acting at the American Academy of Dramatic Arts, and ...
Tell me a bio of Bridget Moynahan.
- Bridget Moynahan is American. ✓
- Bridget Moynahan is an actress. ✓
- Bridget Moynahan is a model. ✓
- Bridget Moynahan is a producer. ✗
- She is best known for her roles in Grey's Anatomy. ✗
- She is best known for her roles in I, Robot. ✓
- She is best known for her roles in Blue Bloods. ✓
- She studied acting. ✓
- She studied at the American Academy of Dramatic Arts. ✗
- ...
66.7%
Stable LM
Bridget Moynahan is an American filmmaker and writer. She is best known for her work on the soap opera General Hospital, which she co-created with husband Charles Kelly. Moynahan was raised in a middle-class family in Los Angeles, ...
- Bridget Moynahan is American. ✓
- Bridget Moynahan is a filmmaker. ✗
- Bridget Moynahan is a writer. ✗
- She is best known for her work on General Hospital. ✗
- General Hospital is the soap opera. ✗
- She co-created General Hospital. ✗
- She co-created General Hospital with her husband. ✗
- Her husband is Charles Kelly. ✗
- Moynahan was raised in a middle-class family. ✗
- Moynahan was raised in Los Angeles. ✗
- ...
10.0%

Figure 1: An overview of FACTSCORE, a fraction of *atomic facts* (pieces of information) supported by a given knowledge source. FACTSCORE allows a more fine-grained evaluation of factual precision, e.g., in the figure, the top model gets a score of 66.7% and the bottom model gets 10.0%, whereas prior work would assign 0.0 to both. FACTSCORE can either be based on human evaluation, or be automated, which allows evaluation of a large set of LMs with no human efforts.

In summary, our contributions are as follows.

1. We introduce FACTSCORE, a new evaluation of factual precision of LMs by breaking their generations into atomic facts and validating each against a given knowledge source. Human evaluation reveals that the state-of-the-art LMs with and without search have low FACTSCOREs.
2. We introduce a model that approximates FACTSCORE with an error rate of $< 2\%$, allowing evaluation of a large set of new LMs without manual human efforts.
3. We will open-source our data as well as FACTSCORE as a Python package for public use. We suggest future work to extend FACTSCORE for a broader set of generations (e.g., open-ended generation) and to further improve the estimator.

2 Related Work

Factual precision in text generation. Factual precision in text generation has been an active area of research in NLP. Most prior work studies factual precision of models supervised for a specific problem such as dialogue (Shuster et al., 2021), or focuses on question answering with short answers (Kadavath et al., 2022; Kandpal et al., 2022; Mallen et al., 2022; Nori et al., 2023).

More recent work has studied factual precision of text generation beyond short answers. Lee et al. (2022) evaluates the factual precision with proxy metrics, e.g., whether named entities in a generation appear in an article of the topic. Gao et al. (2022) and Liu et al. (2023a) verify the precision of the citations (attributions) provided by the model. A concurrent work by Manakul et al. (2023) automates the identification of factual errors in LM generations without using any knowledge source; we use their method as a baseline estimator in Section 4. In contrast, our work (1) considers much

[2] perplexity.ai

longer text generation[3] from a variety of state-of-the-art LMs with and without search, (2) provides their fine-grained evaluation both by human experts and through an automated evaluator that closely approaches humans, and (3) applies it to a large set of LMs at scale.

Fact Verification. Our work is closely related to prior work on fact verification (Thorne et al., 2018; Wadden et al., 2020) where claim sentences are automatically checked against a large knowledge source like Wikipedia or scientific literature. Most literature assumes a single, atomic claim, sometimes modeled with surrounding context (Nakov et al., 2018; Mihaylova et al., 2019; Shaar et al., 2022). There also has been work that verifies a longer sentence or text through decomposition to atomic facts (Fan et al., 2020; Wright et al., 2022; Chen et al., 2022; Kamoi et al., 2023) from which we take inspiration. The primary difference between fact verification literature and our work is that we focus on long-form *model-generated* text rather than sentence-level human-written claims.

Model-based Evaluation. Prior work has used learned models to define automated evaluation scores (Zhang et al., 2020; Liu et al., 2023b). This includes model-based evaluation in summarization that considers the consistency between a summary and a source document using QA or NLI (Kryscinski et al., 2020; Wang et al., 2020; Fabbri et al., 2022; Deutsch et al., 2021; Laban et al., 2022). We take inspiration from this work, and evaluate factual precision of LM generations by considering whether pieces of information are supported by a large text corpus.

3 FActScore: Evaluating Factual Precision of Long-form Text Generation

We introduce FActScore, a new evaluation of an LM that considers the factual precision of atomic facts generated by the LM. We perform human evaluations to calculate FActScores of the state-of-the-art LMs (Section 3.2) and discuss results (Section 3.3). FActScore allows rigorous and fine-grained evaluation of factual precision, but is time-consuming and costly, motivating automatic evaluation in Section 4.

3.1 Definition

FActScore is based on two key ideas.

Key idea 1: Atomic fact as a unit. Long-form text consists of many pieces of information that can each be either true or false. Prior work has explored using a sentence as a unit; however, even a single sentence is a mix of supported and unsupported facts, e.g., in 40% of the cases with ChatGPT. Previous and concurrent work either (1) defines an additional label of `partial support` (Manakul et al., 2023; Liu et al., 2023a) whose definition may be subjective and can lead to low agreement, or (2) takes the strictest definition of `support` that requires every piece of information to be supported (Rashkin et al., 2021; Gao et al., 2022), which ignores the partial support cases, e.g., assigning 0.0 to both generations in Figure 1 even though the first generation is considerably more accurate than the second.

In this paper, we define an atomic fact as a short sentence conveying one piece of information (examples in Figure 1), similar to summarization content units (Nenkova and Passonneau, 2004). An atomic fact is a more fundamental unit than a sentence for a piece of information and provides a more fine-grained evaluation, e.g., in Figure 1, rating the first generation higher than the second.

Key Idea 2: Factual precision as a function of a given knowledge source. Prior work often considers factual precision as a single global truth (Manakul et al., 2023). In contrast, we adopt a perspective that the truthfulness of a statement should depend on a particular knowledge source that end users consider to be trustworthy and reliable. Therefore, instead of whether an atomic fact is globally true or false, we consider whether it is *supported* by a given source of knowledge. This has been used in the fact verification literature (Wadden et al., 2022) where conflict of information between different sources is relatively common.

Definition. Let $\mathcal{M}$ be a language model to be evaluated, $\mathcal{X}$ be a set of prompts, and $\mathcal{C}$ be a knowledge source. Consider a response $y = \mathcal{M}_x$ for $x \in \mathcal{X}$ and $\mathcal{A}_y$, a list of atomic facts in y. A FActScore

[3] Consisting of 110–151 words (Table 1), in contrast to 18–29 in Gao et al. (2022) and 65 in Liu et al. (2023a).

of $\mathcal{M}$ is defined as follows.

$$f(y) = \frac{1}{|\mathcal{A}_y|} \sum_{a \in \mathcal{A}_y} [a \text{ is supported by } \mathcal{C}],$$

$$\text{FACTSCORE}(\mathcal{M}) = \mathbb{E}_{x \in \mathcal{X}}[f(\mathcal{M}_x) | \mathcal{M}_x \text{ responds}].$$

$\mathcal{M}_x$ *responds* means $\mathcal{M}$ did not abstain from responding to the prompt x. This definition assumes the following:

1. Whether or not an atomic fact is supported by $\mathcal{C}$ is undebatable.
2. Every atomic fact in A_y has an equal weight of importance, following Krishna et al. (2023).
3. Pieces of information in $\mathcal{C}$ do not conflict or overlap with each other.

In the rest of the paper, we propose to use people biographies as $\mathcal{X}$ and Wikipedia as $\mathcal{C}$ because they satisfy these assumptions to a reasonable degree (Section 3.2). We discuss in which cases these assumptions hold or may not hold in more detail in the Limitation section.

FACTSCORE considers *precision* but not *recall*, e.g., a model that abstains from answering too often or generates text with fewer facts may have a higher FACTSCORE. We leave factual recall for future work (more discussion in the Limitation section).

3.2 Studied LMs & Data

We perform human evaluation of factual precision based on our definition. We evaluate three LMs (referred to as LM$_{\text{SUBJ}}$, an LM as a subject): (1) **InstructGPT** (`text-davinci-003`, updated from Ouyang et al. (2022)), (2) **ChatGPT** (OpenAI, 2022), and (3) **PerplexityAI**,[2] which incorporates a search engine with a language model. We prompt the LM$_{\text{SUBJ}}$ to generate *people biographies* and evaluate them against Wikipedia for the following reasons.

- Biographies are objective (not subjective or debatable) and contain specific (not vague) information, satisfying Assumption 1.
- Biographies allow evaluation across diverse nationalities, professions, and levels of rarities.
- Wikipedia offers reasonable coverage of information about people and is reasonably self-consistent, satisfying Assumption 3.

We carefully design an annotation pipeline to assign a factual precision to a long-form generation. See Appendix A.3 for details.

3.3 Results

Statistics of the data are reported in Table 1.

All LM$_{\text{SUBJ}}$s struggle with factual precision errors. Factual precisions of InstructGPT and ChatGPT are 42.5% and 58.3%, respectively. PerplexityAI, which uses a commercial search engine and thus should have perfect precision if directly copying the text from the correct Wikipedia page, has a factual precision of 71.5%. We qualitatively analyze their error cases in Appendix A.5.

ChatGPT and PerplexityAI often abstain from answering which presumably improves their factual precision. InstructGPT rarely abstains from answering, likely because it is not trained to do so.

Table 1: Statistics of the data. InstGPT and PPLAI respectively refer to InstructGPT and PerplexityAI. *% responding* indicates % of generations that do not abstain from responding. *# tokens* is based on white space.

	InstGPT	ChatGPT	PPLAI
Use search	✗	✗	✓
% responding	99.5	85.8	90.7
# tokens / response	110.6	154.5	151.0
# sentences / response	6.2	7.9	9.8
# facts / response	26.3	34.7	40.8
Statistics of the labels			
`Supported`	42.3	50.0	64.9
`Not-supported`	43.2	27.5	11.1
`Irrelevant`	14.0	8.3	14.8
Abstains from answering	0.5	14.2	9.3
FACTSCORE	**42.5**	**58.3**	**71.5**

Irrelevant facts either (a) have dependencies on previous facts in a generation that turn out to be unsupported, or (b) are irrelevant to the prompt independent from other facts in a generation (examples in Appendix A.4). We find that (b) rarely happens with InstructGPT and ChatGPT but happens

Table 2: Results on **Error Rate (ER)** along with FACTSCOREs estimated by each model (**FS**). '*retrv*' indicates whether or not retrieval is being used, and '*ranking*' ✓ indicates whether the ranking between three LM_{SUBJ}s rated by the model is consistent to the ground truth ranking. $+$ and $-$ respectively indicate the estimation is an overestimation and an underestimation by more than 5% in absolute. **Red Bold** indicates the best (lowest) ER. See Appendix B.2 for the results in other metrics that consider individual judgments instead of aggregated ones.

	Evaluator	retrv	SUBJ: InstGPT		SUBJ: ChatGPT		SUBJ: PPLAI		ranking
			ER	FS	ER	FS	ER	FS	
	Human		42.5		58.3		71.5		
Trivial	Always Supported		57.5	100.0 +	41.7	100.0 +	28.5	100.0 +	✗
	Always Not-supported		42.5	0.0 −	58.3	0.0 −	71.5	0.0 −	✗
	Always Random		7.5	50.0 +	8.3	50.0 −	21.5	50.0 −	✗
I-LLAMA	No-context LM	✗	7.1	49.6 +	7.8	50.5 −	34.7	36.8 −	✗
	NP	✓	14.8	57.3 +	13.7	72.0 +	1.4	72.9	✓
	Retrieve→LM	✓	14.1	56.6 +	17.1	75.4 +	**0.1**	71.6	✗
	Retrieve→LM + NP	✓	**1.4**	41.1	**0.4**	58.7	9.9	61.6 −	✓
ChatGPT	No-context LM	✗	39.6	82.1 +	31.7	90.1 +	3.3	74.8	✗
	Retrieve→LM	✓	5.1	47.6 +	6.8	65.1 +	0.8	72.3	✓
	Retrieve→LM + NP	✓	5.2	37.3 −	4.7	53.6	8.7	62.8 −	✓

considerably with PerplexityAI, because PerplexityAI often directly copies search results even if they are largely irrelevant to the input prompt. This is in agreement with a concurrent work from Liu et al. (2023a) that shows generative search engines like PerplexityAI copy incorrect search results and generate text that is irrelevant to the input query.

Error rates are higher for rarer entities. Figure 2 (top) shows factual precision over varying frequency levels of topic entities (humans) in the pretraining corpora (see Appendix A.1). There is a notable decrease in FACTSCORE as the rarity of entities increases, consistently across all LM_{SUBJ}s. This is in agreement with Kandpal et al. (2022) and Mallen et al. (2022) which show that short question answering (QA) accuracy is highly correlated with the entity frequencies in the pretraining data. However, in contrast to Kandpal et al. (2022) and Mallen et al. (2022) who report QA accuracy of models with retrieval is robust to the rarity of entities, FACTSCORE of PerplexityAI still significantly drops as entities are rarer: a relative drop of 50% and 64% observed at the atomic-level and sentence-level, respectively.

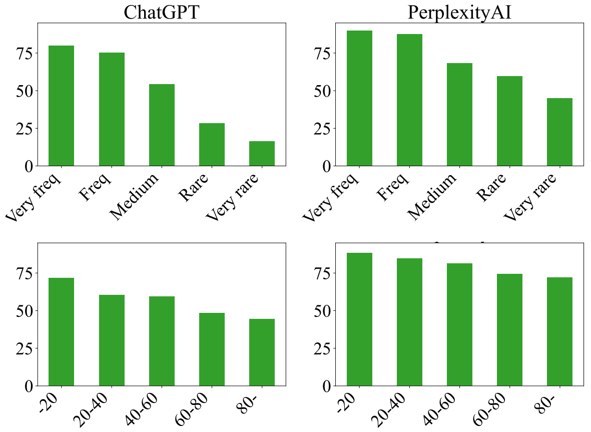

Figure 2: FACTSCORE across varying frequency levels of human entities (**top**) and relative positions in a generation (**bottom**). FACTSCOREs are lower as the rarity of the entities increases and the position of the fact is later.

Error rates are higher for facts mentioned later in the generation. Figure 2 (bottom) reports factual precision over relative positions in a generation. Across all LMs, the later part of the generation has significantly worse precision. This is likely because (a) information mentioned earlier is more frequently mentioned in the pretraining data (e.g., nationality, profession), and (b) error propagation affects the later part of the generation. This also implies that evaluating LMs solely based on short answers may not provide an adequate assessment of their factual precision, as it fails to account for errors that arise in the later stages of generation. More analysis is provided in Appendix A.5.

4 Estimating FACTSCORE for Automatic Evaluation

Human evaluation of factual precision is costly ($4 per generation) (Bohnet et al., 2022; Krishna et al., 2023) because validating every atomic fact against a large knowledge source is time-consuming and one generation contains many (26–41) atomic facts. This prevents LM developers and practitioners from evaluating the factual precision in long-form generation of a new LM_{SUBJ} at scale. In this context, we introduce a model that **estimates** FACTSCORE. This estimator takes a set of generations and automatically computes a FACTSCORE, and can be applied to any LM_{SUBJ}.

We describe our model (Section 4.1) and demonstrate its accuracy against human evaluation (Section 4.2). FACTSCORE estimated by our model is then used to evaluate twelve LMs (Section 4.3).

4.1 Model

Our estimator of FACTSCORE first breaks a generation into a series of atomic facts and then validates each against the given knowledge source. We find taking model-generated atomic facts generated by InstructGPT (used in data collection in Section 3.2) effective and close to human, consistent with findings from prior work (Chen et al., 2022). This section thus focuses on how to validate each atomic fact against a given knowledge source.

The validation is based on zero-shot prompting of an LM referred to as an $\textbf{LM}_{\textbf{EVAL}}$ to distinguish from a LM_{SUBJ}. Specifically, a *prompt*—whose construction methods differ across five variants—is fed into an LM_{EVAL}. The prediction is then made by comparing the conditional probability of `True` and `False` from the LM_{EVAL}. If the logit values are unavailable (e.g., commercial LMs like ChatGPT), the prediction is made based on whether the generated text contains `True` or `False`.[4]

The four variants we consider are as follows. (1) **No-context LM** uses `<atomic-fact> True or False?` as a prompt, closely resembling Kadavath et al. (2022).[5] (2) **Retrieve→LM** retrieves passages from the given knowledge source and then prompts the LM_{EVAL}. It first retrieves k passages, constructs the prompt by concatenating retrieved passages, the given atomic fact, and "`True or False?`", and feeds it to the LM_{EVAL} to get the prediction. (3) **Nonparametric Probability (NP)** makes a judgment based on a nonparametric likelihood. It masks out each token in the atomic fact, computes its likelihood using a nonparametric masked LM (Min et al., 2023), averages probabilities over all tokens, and makes a prediction based on thresholding. (4) **Retrieve→LM + NP** is an ensemble of Retrieve→LM and NP which assigns `Supported` only if both methods assign `Supported`.

We use LLAMA 7B trained on Super Natural Instructions (Inst-LLAMA, Touvron et al., 2023; Wang et al., 2022) and ChatGPT as an LM_{EVAL}, and Generalizable T5-based Retrievers (GTR, Ni et al. (2022)) for passage retrieval. See Appendix B.1 for more implementation details.

4.2 Evaluation of Estimators

Metrics. We report **Error Rate (ER)**—the difference between the ground truth and the estimated FACTSCORE—as well as whether the estimated FACTSCOREs preserve the ranking between three LM_{SUBJ}s. Appendix B.2 discusses results with other metrics that consider individual judgments instead of aggregated judgments. We use the data in Section 3.2 as evaluation data.

Results are reported in Table 2.

Retrieval significantly helps. Models that use retrieval are consistently better than No-context LM which either has a significantly high ER or does not preserve ranking between three LM_{SUBJ}s. This is likely because the LM_{EVAL} has not memorized every factual information about the topic entity, thus benefiting from retrieval providing factual context. Nonetheless, just using Retrieve→LM may overestimate FACTSCORE, e.g., by up to 17% with Inst-LLAMA, when a LM_{SUBJ} is InstructGPT or ChatGPT. In this case, ensembling Retrieve→LM and NP reduces an error rate by a significant

[4] In Appendix B.3, we compare with an alternative prompting that generates a question and compares the answer to it and the expected answer (Kryscinski et al., 2020; Wang et al., 2020; Gao et al., 2022; Manakul et al., 2023). We empirically find our prompting better due to a lack of control over the questions being generated.

[5] In Appendix B.3, we also compare with Self-check LM, a concurrent work from Manakul et al. (2023). We do not include it in the main paper because it has strong restrictions, e.g., requires access to the LM_{SUBJ} at evaluation time and cannot be applied to PerplexityAI with nondeterministic outputs.

Table 3: A set of twelve LMs evaluated in Section 4.3. All models are tuned for instruction following or chat. *Use other LMs* indicates whether the model is trained on any data that includes outputs of another model. *Open* indicates model weights are publicly available.

LM$_{\text{SUBJ}}$	Base LM	Use other LMs	Open	Release
InstructGPT	?	?	✗	Nov 2022
ChatGPT	?	?	✗	Nov 2022
GPT-4	?	?	✗	Mar 2023
Alpaca {7B,13B,65B}	LLAMA	InstructGPT	✓	Mar 2023
Vicuna {7B,13B}	LLAMA	ChatGPT	✓	Mar 2023
Dolly 12B	Pythia 12B	N/A	✓	Mar 2023
Oasst-pythia 12B	Pythia 12B	N/A	✓	Mar 2023
StableLM-tuned 7B	StableLM-base	ChatGPT, GPT-4	✓	Apr 2023
MPT Chat 7B	MPT 7B	ChatGPT	✓	May 2023

margin. When a LM$_{\text{SUBJ}}$ is PerplexityAI, single methods (either Retrieve→LM or NP) give a low ER, and ensemble methods have a higher ER due to an underestimation of FACTSCORE.

ChatGPT is not always the best. One interesting finding is that ChatGPT is not necessarily better than Inst-LLAMA. We investigate this further in Appendix B.3. In summary, ChatGPT is better at validating each individual atomic fact. However, most errors from ChatGPT are incorrectly assigning `Supported` to unsupported facts, overestimating FACTSCORE. In contrast, LLAMA+NP is not biased toward overestimation or underestimation of the factual precision, resulting in an aggregated factual precision to be closer to the ground truth. This is similar to the trade-off between system-level and segment-level correlations in summarization evaluation, which often produce different rankings (Bhandari et al., 2020; Deutsch et al., 2021).

The best estimator depends on the LM$_{\text{SUBJ}}$. While using retrieval is consistently better than No-context LM, the best variant of estimator depends on a LM$_{\text{SUBJ}}$: LLAMA+NP for InstructGPT and ChatGPT, and ChatGPT for PerplexityAI. Nevertheless, both evaluators give consistently correct ranking between three LM$_{\text{SUBJ}}$s, and Section 4.3 show scores from two estimators are largely correlated across 10+ LM$_{\text{SUBJ}}$s (0.99 Pearson's r). We recommend users try both variants of our estimator when evaluating a new LM$_{\text{SUBJ}}$ and report their correlation.

4.3 Evaluation of New LMs

Our estimator allows evaluating factual precision of a large set of new LMs at scale with no human efforts. As a case study, we evaluate ten new LMs that came out within two months at the time of conducting experiments (Table 3). These LMs were evaluated on many benchmarks but not in factual precision of long-form generation since such evaluation is costly. We aim to provide new insights on these LMs by estimating FACTSCORE of their long-form generations.

4.3.1 Setup

We evaluate the following models (Table 3). **GPT-4** (OpenAI, 2023) is a multimodal LM released by OpenAI available through an API. **Alpaca** (Taori et al., 2023) is based on LLAMA (Touvron et al., 2023) fine-tuned on the instructions data based on InstructGPT following the recipe from Wang et al. (2022). **Vicuna** (Chiang et al., 2023) is based on LLAMA fine-tuned on the outputs from ChatGPT available through ShareGPT.[6] **Dolly**[7] is Pythia 12B (Biderman et al., 2023) fine-tuned on DataBricks Dolly, human-written data created by Databricks.[8] **Oasst-pythia**[9] is Pythia 12B fine-tined on human-written data collected through Open Assistant.[10] **StableLM-tuned-alpha**[11] is based on StableLM-base-alpha[12] fine-tuned on the data used in the Alpaca data, DataBricks Dolly, the ShareGPT data, the GPT4All data (Anand et al., 2023) and Anthropic HH (Bai et al., 2022). **MPT Chat** is based on MPT 7B[13] fine-tuned on the ShareGPT data, the Alpaca data, Anthropic HH, HC3 (Guo et al., 2023), and Evol-Instruct.[14]

[6] `sharegpt.com` [7] `dolly-v2-12b` [8] `databricks.com` [9] `oasst-sft-1-pythia-12b` [10] `open-assistant.io`
[11] `StableLM-tuned-alpha-7b` [12] `stablelm-base-alpha-7b` [13] `mosaicml.com/blog/mpt-7b`
[14] `evol_instruct_70k`

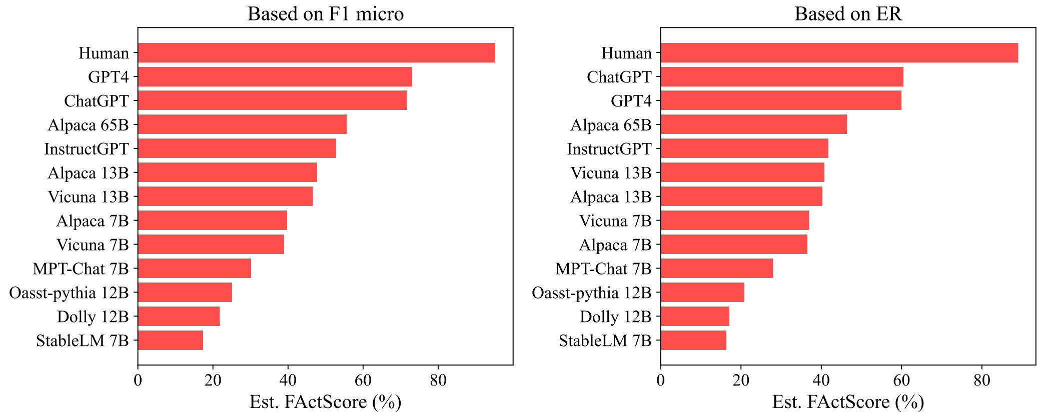

Figure 3: Ranking between 13 subjects (human and 12 LMs), rated by our estimator with the best $\mathrm{F1}_{\mathrm{MICRO}}$ (**left**) and the best ER (**right**): ChatGPT and LLAMA+NP, both with retrieval, respectively. Scores from two metrics have a Pearson's r of 0.99. See Table 4 for % of responding and # of atomic facts per response of each LM. The variance in estimation based on different subsets of prompts is reported in Figure 5 of Appendix B.4.

We prompt each $\mathrm{LM}_{\mathrm{SUBJ}}$ to generate biographies of 500 human entities as done in Section 3.2 but with no overlap in entities. We additionally include InstructGPT, ChatGPT, and human-written biographies obtained through DBPedia. Human-written biographies were unavailable for 11% of entities which we consider as abstaining from responding. See Table 4 for their statistics. In total, we evaluate 6,500 generations from 13 subjects, which would have cost $26K if they were evaluated by humans.

4.3.2 Results

Figure 3 shows the ranking between 13 subjects provided by two variants of the estimator with the best $\mathrm{F1}_{\mathrm{MICRO}}$ and the best ER. Scores from two metrics are largely correlated, having a Pearson's r of 0.99. This evaluation allows a better understanding of these models, including:

Table 4: Statistics of 500 model-generated bios in our unlabeled data from 12 LMs as well as human-written bios. *% responding* indicates % of generations that do not abstain from responding. *#facts / res* indicates # of atomic facts per response. LMs are sorted based on # of facts per response. See Figure 3 for their FACTSCOREs.

$\mathrm{LM}_{\mathrm{SUBJ}}$	% responding	#facts / res
GPT-4	88.2	60.8
Vicuna 13B	76.6	50.9
Vicuna 7B	91.0	45.6
Oasst-pythia 12B	100.0	39.7
StableLM-tuned-alpha 7B	66.6	38.0
MPT Chat 7B	88.8	37.3
ChatGPT	84.2	37.0
InstructGPT	99.8	27.7
Dolly 12B	100.0	24.6
Alpaca 7B	100.0	17.4
Alpaca 65B	100.0	17.1
Alpaca 13B	100.0	16.6
Human	88.8	29.0

- All LMs are substantially less factual than humans. This is in contrast to prior work that claims LMs approach human performance, even for complex tasks (Ding et al., 2022; Nori et al., 2023; Lee et al., 2023), even though the task of writing biographies is fairly easy.
- GPT-4 and ChatGPT are comparable in factual precision. However, GPT-4 abstains from responding less (12% vs. 16%) and generates significantly more facts (61 vs. 37 per response).
- GPT-4 and ChatGPT are significantly more factual than public models.
- Within the same family of models that differ in sizes, there is a clear correlation between the model size and factual precision, e.g., Alpaca 65B > 13B > 7B, and Vicuna 13B > 7B.
- Alpaca and Vicuna achieve performance that is very close to each other within the same size of models, possibly because they share the same base model and similar training data. Nonetheless, Vicuna generates significantly more atomic facts than Alpaca does (51 vs. 17 per response). Also, Alpaca never abstains from answering while Vicuna does.
- Within public models, there are large gaps in factual precision even when the model size is similar, e.g., within the 7B models, Alpaca and Vicuna ($\sim 40\%$) are more factual than MPT-Chat (30%)

and StableLM (17%). Possible factors include the choice of the base LM, the data, and the training recipe (Hoffmann et al., 2022).

- As a random fun fact, Dolly 12B mentions Databricks 26 times, e.g., "`Zubaira Tukhugov is the founder and CEO of Databricks, a pioneer in the artificial intelligence ecosystem.`" (Zubaira Tukhugov is a mixed martial artist with no connection to Databricks.) This is possibly because the data manually created by Databricks on which Dolly 12B is trained includes much data about Databricks.

We highlight that this evaluation only considers factual precision, specifically in people biographies. A holistic evaluation of LMs should include other aspects of generations such as fluency, coherence, relevance, consistency and creativity, which is out of scope for this paper.

5 Conclusion and Future Work

We introduced FACTSCORE, a new evaluation of the factual precision of long-form generation from LMs that breaks a generation down into a series of atomic facts and computes a fraction of facts supported by a given knowledge source. We first performed extensive human evaluation, finding that commercial, state-the-art-art LMs—InstructGPT, ChatGPT, and search engine augmented, PerplexityAI—make a substantial amount of errors, e.g., having a FACTSCORE of 58% in the case of ChatGPT. Since human evaluation is time-consuming and costly, we proposed a model that estimates FACTSCORE, allowing an automatic evaluation of factual precision. We found our estimator based on retrieval over a knowledge source and competitive language models estimates the factual precision close to the ground truth, and showcased its application by evaluating 12 recently-released LMs that could have cost $65K if evaluated by humans and providing insights about them.

Limitations

Scope of FACTSCORE. All of our experiments focus on people biographies and Wikipedia, because many LMs can generate biographies with objective and specific facts (rather than subjective and vague ones) and Wikipedia has a high coverage for them. We highlight that FACTSCORE can be applied to a broader domain, e.g., text about recent events whose knowledge source can be a collection of news articles, or text about scientific findings whose knowledge source can be a collection of scientific literature.

Due to the assumptions made in Section 3.1, FACTSCORE is not applicable when the facts are more nuanced, open-ended, and debatable (Chen et al., 2019; Xu et al., 2023) or with a knowledge source whose text frequently conflicts with each other (Wadden et al., 2022). Moreover, FACTSCORE may not be suitable for the human-written text that is nuanced and includes intentional or implicit deception.

Limitation in our estimator. While our estimator closely approximates humans and provides consistent ranking over a large set of LMs, it is not perfect in individual judgments, and the best variant depends on the degree of how close a generation is to human-written text and its linguistic complexity. Future work can investigate how the distribution of model generation affects the performance of the estimator and further improve the estimator.

Beyond factual precision. FACTSCORE focuses on factual precision—whether each piece of information in a generation is factually supported by a reliable source of knowledge—which is only one aspect of the broader factuality problem. For instance, FACTSCORE does not consider factual recall: the coverage of information in a generation. FACTSCORE does not penalize a model that abstains from responding too frequently or generates fewer facts, which can be unfair since there is an inherent trade-off between precision and recall. Moreover, the boundary between precision and recall is often blurry, e.g., it is possible that, even if every piece of information in a generation is supported, it misses a significant piece of information that should have been mentioned. We leave a more holistic evaluation of factuality for future work, and recommend reporting FACTSCORE together with the % of abstention and the average number of atomic facts (as we did in Section 4.3).

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A Details in Data Collection

A.1 Sampling human entities

We sample 183 human entities to be annotated as follows. We first choose entities from Wikidata whose `instance of` is `human` and have corresponding Wikipedia pages. We then categorize entities based on two dimensions: frequency and nationality, resulting in 20 categories. We then sample entities uniformly at random over all categories.

Frequency. We compute `freqValue` as a maximum of the entity occurrence in Wikipedia provided by Kandpal et al. (2022) and the pageview count of the Wikipedia page following Mallen et al. (2022). We found using one of them could lead to an underestimate of frequency levels due to failure in entity linking or mismatch in the Wikipedia page title, and taking a maximum of them provides a reasonable solution. We then assign one of five categories: 'Very rare' if `freqValue`$\in [0, 10^2)$, 'Rare' if `freqValue`$\in [10^2, 10^3)$, 'Medium' if `freqValue`$\in [10^3, 10^4)$, 'Frequent' if `freqValue`$\in [10^4, 10^5)$, and 'Very frequent' if `freqValue`$\in [10^5,)$.

Nationality. We take `country of citizenship` from Wikidata and assign them one of four categories: 'North America', 'Europe & Middle East', 'Asia & Pacific' and 'Latin/South America & Africa'.

A.2 Details in generating atomic facts

We break out a generation automatically by splitting a generation into sentences, and feeding each sentence to InstructGPT (`text-davinci-003`) with a series of instructions to further break it down to a series of atomic facts. The prompt to InstructGPT is provided in Table 15. Outputs from InstructGPT are used (1) to human experts for revision (Section 3.2) and (2) for model-based evaluators (Section 4). We find human experts split and merged atomic facts from InstructGPT for 18% and 34% of the cases, respectively.

A.3 More details on data collection

We carefully design an annotation pipeline to assign a factual precision to a long-form generation through the following steps.

Step 0: Sampling people entities. We sample 183 people entities from Wikidata who have corresponding Wikipedia pages. We sample entities to annotate from a uniform distribution over categories defined in Appendix A.1.

Step 1: Obtaining generations. We feed a prompt "`Tell me a bio of <entity>`" to the LM_{SUBJ} and take a generation as it is. We implement rules to identify generations that abstain from answering and filter them out.

Step 2: Atomic facts generation. Human annotators break a generation into a series of atomic facts. To save annotation time, we provide atomic facts broken down by InstructGPT which human annotators can take and revise. Details in Appendix A.2.

Step 3: Labeling factual precision & editing. We ask another set of human annotators to assign each atomic fact one of three labels. If the atomic fact is clearly not related to the prompt, and thus should be removed from the bio without a validation step, they assign `Irrelevant`. If the fact is relevant, they validate the fact based on the English Wikipedia, and label either `Supported` or `Not-supported`.

We recruit freelancers through Upwork and pay 15–25 USD per hour. We recruit fact-checking experts—freelancers who mentioned fact-checking as their expertise—for Step 3. Every worker went through a qualification test of 2 hours and was tested to be highly qualified. We design one HIT to consist of three generations, one from each LM_{SUBJ}, for one prompt, because we find it saves annotation time in total. 10% of the HITs have two workers assigned to calculate the agreement rate; the rest have one worker assigned. The agreement rates are 96%, 90% and 88% for InstructGPT,

Table 5: Examples that contain `Supported`, `Not-supported` and `Irrelevant`. Sentences in bullet points indicate atomic facts.

Prompt: Tell me a bio of Ylona Garcia.
Sentence: [Ylona Garcia] has since appeared in various TV shows such as ASAP (All-Star Sunday Afternoon Party), Wansapanataym Presents: Annika PINTAsera and Maalaala Mo Kaya.

- Ylona Garcia has appeared in various TV shows. `Supported`
- She has appeared in ASAP. `Supported`
- ASAP stands for All-Star Sunday Afternoon Party. `Supported`
- ASAP is a TV show. `Supported`
- She has appeared in Wansapanataym Presents: Annika PINTAsera. `Not-supported`
- Wansapanataym Presents: Annika PINTAsera is a TV show. `Irrelevant`
- She has appeared in Maalaala Mo Kaya. `Not-supported`
- Maalaala Mo Kaya is a TV show. `Irrelevant`

Prompt: Tell me a bio of John Estes.
Sentence: William Estes is an American actor known for his role on CBS police drama Blue Bloods as Jameson J̈amieR̈eagan.

- William Estes is an American. `Irrelevant`
- William Estes is an actor. `Irrelevant`
- William Estes is known for his role on CBS police drama Blue Bloods. `Irrelevant`
- William Estes' role on Blue Bloods is Jameson "Jamie" Reagan. `Irrelevant`

ChatGPT and PerplexityAI, respectively. Appendix A.5 discusses disagreement cases in more detail. The full instructions and the interface are provided in Figure 6 and Figure 7, respectively.

A.4 Examples in annotated data

Table 5 provides examples of the human-annotated data, each atomic fact with an assigned label. `Supported` and `Not-supported` respectively indicate Wikipedia supports the fact and does not support the fact (either contradicts or does not contain any evidence). `Irrelevant` indicates the fact is irrelevant to the input prompt, which can further be divided into two cases: (1) the fact depends on other facts because it expands previous facts in a generation, and such other facts are `Not-supported`, e.g., in the first example in Table 5, and (2) the entire sentence is irrelevant to the prompt, independent from other facts in a generation, e.g., the second example in Table 5. The second case rarely happens with InstructGPT and ChatGPT, but happens considerably with PerplexityAI, i.e., 24.7% of generations of PerplexityAI have $\geq$ sentences marked as irrelevant without dependencies to other facts, compared to 0.5% and 1.3% in InstructGPT and ChatGPT, respectively. This is because PerplexityAI often directly copies search results even if they are largely irrelevant to the input prompt. This is in agreement with a concurrent work from Liu et al. (2023a) that shows generative search engines like PerplexityAI copy incorrect search results and generate text that is irrelevant to the input query.

A.5 Qualitative Analysis

Qualitative analysis of `Not-supported`. One of the surprising findings is that a FActScore of PerplexityAI (71.5%) is lower than expected despite using the search engine. To better understand its errors, we categorize 30 random samples whose label is `Not-supported`. The top three categories are shown in Table 8 (see Appendix A.5 for the full categorization).

1. A single sentence from Wikipedia providing a direct contradiction to the generation (43.3%)
2. Errors found after reading the entire page, often because the fact that should have been mentioned in Wikipedia if true is missing (23.3%)
3. The generation is subjective, often because it copies subjective text from Wikipedia, e.g., copying a quote from a journalist without realizing it (16.7%).

We also find that, although PerplexityAI provides citations to the references, citations have little correlation with factual precision. 36.0% and 37.6% of supported and unsupported sentences have citations, respectively. Together with independent findings from Liu et al. (2023a), this indicates that commercial LMs that incorporate search and provide citations may not be as reliable as expected.

Analysis of `Not-supported`. This section provides the full categorization of `Not-supported` cases of PerplexityAI, summarized in Section 3.3. Table 6 shows examples of each category.

Table 6: Categorization of precision errors (Not-supported) from PerplexityAI (Section A.5). Gen indicates the generation from PerplexityAI, and Wiki indicates evidence text from Wikipedia. Comment indicates our comments.

Category	%	Example
Single-sentence contradiction (words)	33.3	Gen On November 25th, 2023, Glover Teixeira became an American citizen. Wiki In November 2020, Teixeira became an American citizen. Gen [Eric Hacker] was named the International League Pitcher of the Year. Wiki [Eric Hacker] was named the IL Pitcher of the Week.
Single-sentence contradiction (beyond words)	10.0	Gen William Waldegrave's grandfather was James II and VII. Wiki His father's title was created ... for the diplomat and ambassador James Waldegrave, 1st Earl Waldegrave, whose grandfather was James II and VII. Gen She has appeared in several successful films such as (...) and Zero (2018). Wiki: Zero was a commercial failure.
Page-level contradiction	23.3	Gen Some of [Julia Faye's] notable films include ... "Cleopatra" (1934). Comment No mention of *Cleopatra* on the *Julia Faye* page, and no mention of *Julia Faye* on the *Cleopatra* page. Gen [Kang Ji-hwan] has donated money to various charities and organizations over the years. Comment No such mention on the *Kang Ji-hwan* page.
Subjective	16.7	Gen His achievements, as an actor and as a cultural force, will surely prove to be as heroic as those of the characters he portrayed. Wiki Culture writer Steve Rose, in The Guardian, wrote: "Chadwick Boseman began his career playing African American icons and pioneers; he ends it as one himself. His [...] achievements, as an actor and as a cultural force, will surely prove to be as heroic as those of the characters he portrayed."
Fact is irrelevant	3.3	Gen [Zamfir Arbore]'s life is not well-documented, and there is little information available about him.
Wiki is inconsistent & wrong	3.3	Gen Kick (2014) that brought [Sajid Nadiadwala] various debutant director awards. Wiki 2015, IIFA Award for Debut Director, Kick. (...) Kick brought him various debutant director awards. Comment The first text is from a table that indicates he won one award (accurate). The second is inaccurate, incorrectly citing a news article.
Annotation error	10.0	Gen [Zamfir Arbore] was part of the staff of Românul. Wiki The Românul staff came to include Zamfir Arbore. Comment Mentioned in the *Românul* page but not in the *Zamfir Arbore* page.

- Single-sentence contradiction: A single sentence from Wikipedia provides direct contradiction to the generation, either at a word level (numbers, dates, or entities) or beyond.
- Page-level contradiction: Errors found after reading the entire page, often because a fact that should have been mentioned in Wikipedia if true is missing, e.g., whether the subject appears in a particular film.
- Subjective: Generation is subjective, often because PerplexityAI copies subjective text from Wikipedia, e.g., directly copying a quote from a journalist without realizing it.
- Fact is irrelevant: Generation is irrelevant to the subject due to a search error.
- Wiki is inconsistent & wrong: In the example, Wikipedia indicates that the subject won one award from the film Kick, but also includes text that they won multiple awards from Kick, which is inaccurate and cited a news article that does not support the claim.
- Annotation error: Annotators assign incorrect labels, typically because the information is not mentioned in the subject's Wikipedia page (likely because it is insignificant).

Analysis of disagreement cases. We categorize disagreement cases in Table 7. The 70% is due to an inherent debatability on whether or not the fact is supported by a given source of knowledge, not satisfying Assumption 2 in Section 3.1. This is because there can be multiple interpretations of a fact, it is debatable whether or not an information can be inferred from a piece of text, or the atomic fact is subjective. For instance:

- `[subject] is an inventor`: the subject is widely known as an inventor of an object, but later turns out that they did not invent it (instead, commercialized it).
- `[subject] is a producer`: the subject is widely known as another profession (e.g., a singer) but produced one music video.

Table 7: Categorization of disagreement cases. Gen indicates the generation from PerplexityAI, and Wiki indicates evidence text from Wikipedia. Comment indicates our comments.

Category	%	Example
Different interpretations of the factual information	21	Gen Gerhard Fischer is an inventor. Wiki Gerhard Fischer (inventor). ... was first patented by Dr. Gerhard Fischer in 1931. A metal detector had been invented some forty years earlier (1881) by Alexander Graham Bell ... Gen Chadwick Boseman was a producer. Comment Chadwick Boseman is not known as a producer, but produced one music video.
Inferred (not directly mentioned but highly likely)	16	Gen Leach has since become a member of the England Test team. Comment Leach is a member of the England Test team, but since when is less clear.
Depends on how strict in judging the correctness	11	Gen He made his Test debut for England in March 2018. Wiki On 16 March 2018, he was called up to England's Test squad (...) He made his debut in the second Test in Christchurch. Gen The building was the first LEED-certificated building in Edmonton. Wiki (..) became the first project in the City of Edmonton to achieve a LEED Gold status.
Subjective	21	Gen Chadwick Boseman became an African American pioneer. Wiki Culture writer Steve Rose, in The Guardian, said that Boseman's career was revolutionary and he "leaves behind a gamechanging legacy" (...) Rose wrote: "Chadwick Boseman began his career playing African American icons and pioneers; he ends it as one himself."
Wikipedia not consistent	5	Gen [Tim Fischer] was an Ambassador to the Holy See from 2009 to 2012. Wiki ... was later Ambassador to the Holy See from 2009 to 2012. (...) Australian Ambassador to the Holy See 2008–2012 Comment The plain text and the table of the *Tim Fischer* page as well as the *Australian Ambassador to the Holy See* page are inconsistent in his start year.
Two different entities	5	Comment Carlos J. Alfonso vs. Carlos Alfonso
Mistakes in annotation	21	Gen Jack Leach is a left-handed batsman. Comment mentioned in the *England cricket team* page, Table *Current Squad*.

Nonetheless, since our agreement rate is fairly high (91%), we think such cases are rare in our particular domain of people biographies. We include more discussion on other domains that such cases may be more frequent in the Limitation section.

B Details in Estimators

B.1 Implementation details

As an LM$_{\text{EVAL}}$, we use the best open LM and the best commercial LM at the time of conducting experiments: LLAMA 65B (Touvron et al., 2023) and LLAMA 7B trained on Super Natural Instructions (Inst-LLAMA, Wang et al., 2022) as the former, and ChatGPT (OpenAI, 2022) as the latter. For computing nonparametric probabilities, we use a single-mask variant of NPM with BM25 as in the original paper (Min et al., 2023), and use 0.3 as a thresholding hyperparameter.

For passage retrieval, we use Generalizable T5-based Retrievers (GTR, a large variant), an unsupervised dense passage retrieval system (Ni et al., 2022). We restrict retrieved passages to be from the topic entity's page, and use $k = 5$. We find our estimator is not sensitive to the choice of a retrieval system (ablations provided in Appendix B.3). As a retrieval corpus, we use the English Wikipedia from 04/01/2023 which is around the time the data annotation was completed, and split each page into passages with up to 256 tokens.

Additional baselines. We also compare with **Self-check LM**, a method from a concurrent work by Manakul et al. (2023). Self-check LM needs multiple samples generated from the LM$_{\text{SUBJ}}$. It

Table 8: Top three categories of precision errors (`Not-supported`) from PerplexityAI (Section 3.3). See Appendix A.5 for the full results. `Gen` indicates the generation from PerplexityAI, and `Wiki` indicates evidence text from Wikipedia. `Comment` indicates our comments.

Single-sentence contradiction (43.3%)
`Gen` [Eric Hacker] was named the International League Pitcher of the Year. `Wiki` [Eric Hacker] was named the IL Pitcher of the Week.
`Gen` She has appeared in several successful films such as (...) and Zero (2018). `Wiki`: Zero was a commercial failure.
Page-level contradiction (23.3%)
`Gen` Some of [Julia Faye's] notable films include ... "Cleopatra" (1934). `Comment` No mention of *Cleopatra* on the *Julia Faye* page, and no mention of *Julia Faye* on the *Cleopatra* page.
`Gen` [Kang Ji-hwan] has donated money to various charities and organizations. `Comment` No such mention on the *Kang Ji-hwan* page.
Subjective (16.7%)
`Gen` His achievements, as an actor and as a cultural force, will surely prove to be as heroic as those of the characters he portrayed. `Wiki` Culture writer Steve Rose, in The Guardian, wrote: "Chadwick Boseman began his career playing African American icons and pioneers; he ends it as one himself. His [...] achievements, as an actor and as a cultural force, will surely prove to be as heroic as those of the characters he portrayed."

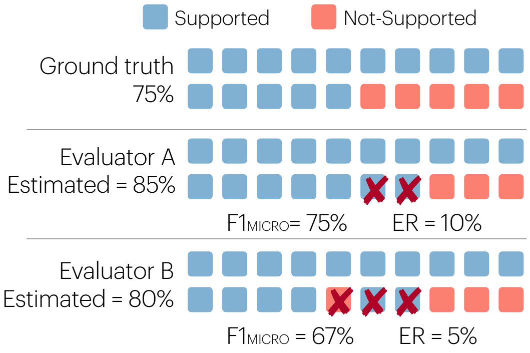


Figure 4: A case in which $\mathrm{F1}_{\text{MICRO}}$ and Error Rate (ER) rank two evaluators differently. Evaluator A is better in $\mathrm{F1}_{\text{MICRO}}$, and Evaluator B is better in ER.

validates the given atomic fact by prompting $\mathrm{LM}_{\text{EVAL}}$ conditioning on each generated sample,[15] making judgment (`Supported` or not) from each, and aggregates the results through a majority vote. This method assumes (1) the $\mathrm{LM}_{\text{SUBJ}}$ is available at the time of evaluation and (2) the outputs from the $\mathrm{LM}_{\text{SUBJ}}$ are nondeterministic, which makes it not applicable to PerplexityAI.

B.2 Segment-level vs. system-level evaluation

Besides how close the estimated FACTSCORE is to the ground truth FACTSCORE (**Error Rate**, as reported in Section 4), we also report $\mathbf{F1}_{\textbf{MICRO}}$. $\mathrm{F1}_{\text{MICRO}}$ evaluates how well the model validates each individual atomic fact, assuming oracle atomic facts (atomic facts by human experts) are given, and evaluates how good the estimator is in identifying facts that are not `Supported` (`NS`). Formally, let $\mathcal{G}$ and $\mathcal{P}$ be sets of atomic facts in a set of generations that have `Not-supported` as a ground truth label and as a predicted label, respectively. We define $\mathrm{F1}_{\text{MICRO}}$ as follows.

$$\mathrm{P} = \frac{\mathcal{P} \cap \mathcal{G}}{\mathcal{P}}, \quad \mathrm{R} = \frac{\mathcal{P} \cap \mathcal{G}}{\mathcal{G}}, \quad \mathbf{F1}_{\text{MICRO}} = \frac{2 \cdot \mathrm{P} \cdot \mathrm{R}}{\mathrm{P} + \mathrm{R}}$$

We call them MICRO because they consider individual decisions rather than aggregated estimation.

ER vs. $\mathbf{F1}_{\textbf{MICRO}}$. $\mathrm{F1}_{\text{MICRO}}$ cares about the individual decision, while ER cares about the aggregated estimation. An evaluator that has a high (better) $\mathrm{F1}_{\text{MICRO}}$ but always overestimates or underestimates factual precision may have a higher (worse) ER, e.g., Evaluator A in Figure 4. Conversely, an evaluator

[15] Manakul et al. (2023) uses BERTScore and a supervised question answering system instead of LM prompting, however, we find LM prompting to be significantly better.

Table 9: Results in **$\mathrm{F1}_{\mathrm{MICRO}}$** using Inst-LLAMA 7B as an $\mathrm{LM}_{\mathrm{EVAL}}$. '*retrv*' indicates whether or not retrieval is used. Self-check is not applicable to PerplexityAI whose outputs are semi-deterministic. **Bold** indicates the best performance.

Evaluator	retrv	$\mathrm{LM}_{\mathrm{SUBJ}}$		
		InstGPT	ChatGPT	PPLAI
Always `Supported`	-	0.0	0.0	0.0
Always `Not-supported`	-	71.4	58.3	30.9
Random	-	52.2	45.0	25.7
No-context LM	✗	61.2	52.2	31.4
Self-check LM	✗	66.0	48.4	-
Retrieve→LM	✓	78.7	61.9	51.1
NP	✓	70.0	56.6	51.4
Retrieve→LM + NP	✓	**83.2**	**70.5**	**53.3**

that has a lower (worse) $\mathrm{F1}_{\mathrm{MICRO}}$ but is not biased toward overestimation nor underestimation may have a lower (better) ER, e.g., Evaluator B in Figure 4. Prior work in model-based evaluation mainly reports aggregated scores since the goal is a comparison between different systems being evaluated (Zhang et al., 2020; Rashkin et al., 2021; Gao et al., 2022) while we report both to see the relationship between two types of metrics. $\mathrm{F1}_{\mathrm{MICRO}}$ and ER are also closely related to *segment*-level and *system*-level correlations to human judgments respectively, which have been extensively used in developing evaluation metrics in machine translation (Ma et al., 2019; Thompson and Post, 2020) and summarization (Bhandari et al., 2020; Deutsch et al., 2021).

Results. Results on $\mathrm{F1}_{\mathrm{MICRO}}$ are reported in Table 9. Self-check LM outperforms no-context LM by 4–11%, which confirms findings from Manakul et al. (2023). However, both significantly underperform methods that use retrieval. This is in contrast to Manakul et al. (2023) that reports that Self-check without retrieval achieves performance that is close to that with retrieval, likely because the data in Manakul et al. (2023) contains more frequent entities. The fact that retrieval significantly helps is consistent with findings in Section 4.2 with an ER as a metric.

Adding NP improves Retrieve→LM by 2–9%, again consistent with findings in Section 4.2. This is likely because Retrieve→LM often makes incorrect predictions when there is a strong bias from an LM or there are distracting passages, and considering nonparametric probabilities makes the model more robust to these factors. For instance, given an unsupported fact `Samuel Oboh is Nigerian`, No-context LM, Self-check LM and Retrieve→LM predict `Supported` due to a strong name-nationality bias. NPM correctly predicts `Not-supported` based on a passage `Samuel Oboh ... is a Canadian architect, manager, ...`. It is also worth noting that this is different from findings in Section 4.2 that ChatGPT is not necessarily better than LLAMA+NP based on ER.

Using a stronger $\mathrm{LM}_{\mathrm{EVAL}}$ significantly improves $\mathrm{F1}_{\mathrm{MICRO}}$. Table 10 reports a comparison across different choices of an $\mathrm{LM}_{\mathrm{EVAL}}$. Within the same method, Inst-LLAMA 7B outperforms LLAMA 65B, and ChatGPT outperforms both. Using retrieval is critical across all models, e.g., the best no-context model based on ChatGPT is underperformed by all models with retrieval. Using NP helps LLAMA-based models but not ChatGPT, likely because ChatGPT is less affected by incorrect prior from the LM or distracting passages.

It is worth noting that these results are somewhat different from findings in Section 4.2 that ChatGPT is not necessarily better than LLAMA+NP. This is becauase, although ChatGPT is better in validating each individual atomic fact, most errors from ChatGPT are incorrectly assigning `Supported` to `Not-supported` facts, resulting in an overestimation of FACTSCORE. In contrast, LLAMA+NP is not biased toward overestimation or underestimation of the factual precision, resulting in an aggregated factual precision to be closer to the ground truth. This is similar to the trade-off between system-level and segment-level correlations in summarization evaluation (Bhandari et al., 2020; Deutsch et al., 2021).

Table 10: Ablation in **F1**$_{\textbf{MICRO}}$ on the choices of LM$_{\text{EVAL}}$. '*retrv*' indicates whether or not retrieval is used. **Bold** and **Red bold** indicate the best F1 within open-access LMs and commercial LMs, respectively.

Evaluator	retrv	LM$_{\text{SUBJ}}$		
		InstGPT	ChatGPT	PPLAI
LLAMA 65B				
No-context LM	✗	22.2	20.0	18.6
Retrieve→LM	✓	54.6	42.1	36.1
Retrieve→LM + NP	✓	80.1	67.1	**55.1**
Inst-LLAMA 7B				
No-context LM	✗	61.2	52.2	31.4
Retrieve→LM	✓	78.7	61.9	51.1
Retrieve→LM + NP	✓	**83.2**	**70.5**	53.3
ChatGPT				
No-context LM	✗	40.0	25.4	25.4
Retrieve→LM	✓	**87.5**	**80.2**	**65.8**
Retrieve→LM + NP	✓	86.6	77.8	60.8

Table 11: Results on F1$_{\text{MICRO}}$, comparing between the QA prompting and TF Prompting. We use Inst-LLAMA 7B as an LM$_{\text{EVAL}}$. Self-check is not applicable to PerplexityAI since PerplexityAI outputs are semi-deterministic. **Bold** indicates the best F1$_{\text{MICRO}}$.

Evaluator	LM$_{\text{SUBJ}}$		
	InstGPT	ChatGPT	PPLAI
Always Supported	30.8	37.1	45.0
Always Not-supported	35.7	29.1	15.5
Random	50.5	50.2	43.2
QA *Prompting*			
No-context LM	56.5	48.8	32.5
Self-check LM	65.3	63.2	-
Retrieve→LM	65.3	58.2	47.3
TF *Prompting*			
No-context LM	57.3	55.3	41.7
Self-check LM	68.0	61.9	-
Retrieve→LM	**78.9**	**71.4**	**69.2**

B.3 Ablations

QA Prompting vs. TF Prompting As described in Section 4.1, we use True or False as part of the prompt, so-called TF Prompting. An alternative is QA Prompting, which generates a question and the expected answer, obtains the answer for the generated question independent from the expected answer, and compares the expected answer and the predicted answer. This approach has been widely studied in the summarization literature and recent work in factual precision (Kryscinski et al., 2020; Wang et al., 2020; Gao et al., 2022; Manakul et al., 2023). Table 11 provides a comparison between two types of prompting. The TF approach significantly outperforms the QA approach, consistently over all methods. Our further analysis finds that this is due to generated questions often being overly vague or ambiguous. For instance, given a supported fact Samuel Oboh is an architect, the LM generates What is Samuel Oboh's job? as a question and Architect as an expected answer, and the obtained answer is Vice President. Although both Architect and Vice President are correct, they are not the same, thus the model incorrectly predicts Not-supported. Such cases make the model overpredict Not-supported, leading to many incorrect predictions.

Impact of the choice of retrieval. Table 12 compares Retrieve→LM methods based on a few passage retrieval systems, including BM25 (Lin et al., 2021), GTR Large and GTR xLarge. Results

Table 12: Results on $\mathrm{F1}_{\text{MICRO}}$, comparing different retrieval systems: BM25, GTR Large and GTR xLarge, all with Retrieve→LM based on Inst-LLAMA 7B. **Bold** indicates the best $\mathrm{F1}_{\text{MICRO}}$.

Retrieval	$\mathrm{LM}_{\text{SUBJ}}$		
	InstGPT	ChatGPT	PPLAI
BM25	78.5	70.8	69.1
GTR Large	78.9	**71.4**	**69.2**
GTR xLarge	**79.2**	71.3	69.0

Table 13: Categorization of 30 samples incorrectly predicted by Retrieve→LM based on ChatGPT.

Category	%
No direct evidence from retrieved passages	70
Distracted by other passages	17
Atomic fact is context-dependent	7
Wrong prediction even with the right passage	3
Annotation error	3

indicate that all retrieval systems are equally good and Retrieve→LM is not sensitive to the choice of the retrieval system.

Qualitative analysis. Table 13 categories errors made by Retrieve→LM based on ChatGPT, the evaluator with the best $\mathrm{F1}_{\text{MICRO}}$. 70% of the errors are due to retrieved passages not providing direct evidence (either support or contradiction). These are difficult even for state-of-the-art retrieval systems and language models because validating facts often requires reading the entire page rather than a single passage, e.g., an actor not appearing in a particular film. 17% of errors are made because ChatGPT is being distracted by other passages, although it assigns a correct label if only a particular, correct passage is given.

B.4 More details in evaluation of new LMs (Section 4.3)

Model description. **GPT-4** (OpenAI, 2023) is a multimodal LM released by OpenAI, available through an API. **Alpaca** (Taori et al., 2023) is based on LLAMA (Touvron et al., 2023) fine-tuned on the Instruction data based on InstructGPT following the Self-Instruct recipe (Wang et al., 2022). **Vicuna** (Chiang et al., 2023) is based on LLAMA fine-tuned on the outputs from ChatGPT available through ShareGPT.[16] **Dolly**[11] is based on Pythia 12B (Biderman et al., 2023) fine-tuned on DataBricks Dolly, human-written data created by Databricks.[12] **Oasst-pythia**[13] is based on Pythia 12B fine-tined on human-written data collected through Open Assistant.[14] **StableLM-tuned-alpha**[15] is based on StableLM-base-alpha[16] fine-tuned on the data used in the Alpaca data, DataBricks Dolly, the ShareGPT data, the GPT4All data (Anand et al., 2023) and Anthropic HH (Bai et al., 2022). **MPT Chat** is based on MPT 7B[17] fine-tuned on the ShareGPT data, the Alpaca data, Anthropic HH, HC3 (Guo et al., 2023), and Evol-Instruct.[18]

Variance in estimation. Figure 5 reports FACTSCOREs estimated by two variants of our estimator as in Figure 3 but with 100 random subsets of the data. Specifically, we chose N samples (out of 500) uniformly at random across 20 categories (defined in Appendix A.1) M times and report the average and the standard deviation. We use $N = \{40, 100, 200\}$ and $M = 100$. Results indicate that the variance is overall low, preserving ranking between 13 subjects in most cases. As expected, the variance is lower as the sample size gets larger. Finally, the estimator based on ER based on LLAMA+NP (bottom) has an overall lower variance than the estimator based on ChatGPT (top).

[16] `sharegpt.com` [11] `dolly-v2-12b` [12] `databricks.com` [13] `oasst-sft-1-pythia-12b` [14] `open-assistant.io` [15] `StableLM-tuned-alpha-7b` [16] `stablelm-base-alpha-7b` [17] `mosaicml.com/blog/mpt-7b` [18] `evol_instruct_70k`

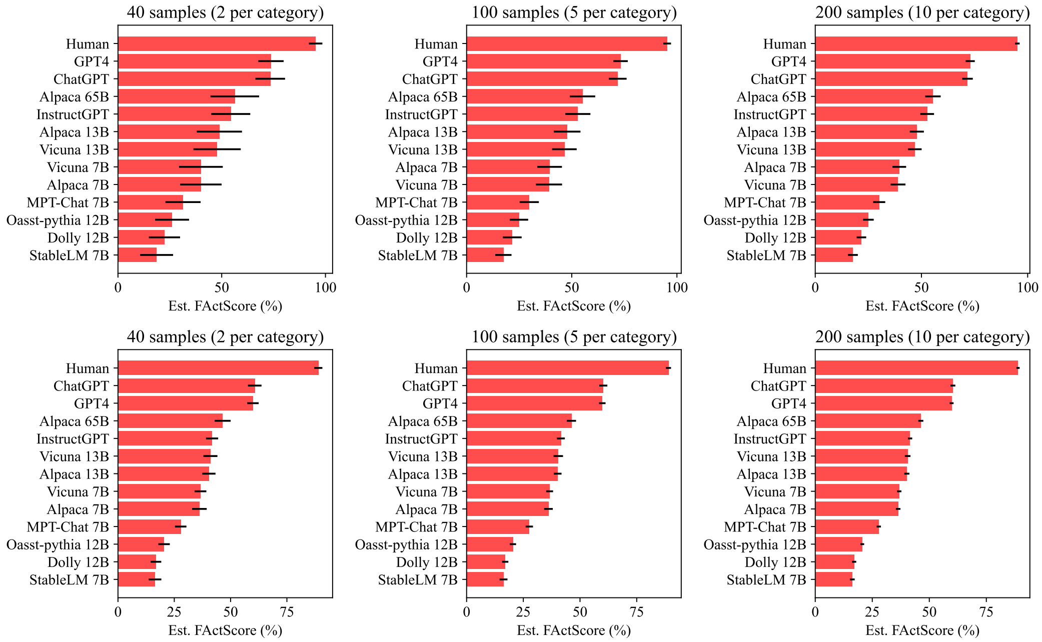


Figure 5: Impact of different subsets of random samples in prompts. The FActScores to 13 subjects (human and 12 LMs) are rated by the two best variants of our estimator: ChatGPT (**Top**) and LLAMA+NP (**Bottom**), both with retrieval. The variance is overall low, and is lower as the sample size gets larger and with LLAMA+NP (bottom) than with ChatGPT (top).

C Editing Experiments

Our experiments in Section 4 focused on automatically identifying factual precision errors in long-form generations by language models. Can these labels be used to actually correct mistakes in the long-form generations? In this section we perform a preliminary exploration of methods to edit long-form LM generations to reflect factually correct information. We assume we have access to the human-annotated set of FActScore labels, and measure how good models are at editing incorrect sentences. In other words, we evaluate our editor models independent of the errors arising from the estimator.

C.1 Methods

We adopt a similar set of methods as Section 4.1 for our editing models. All methods below use four exemplar examples for in-context learning which were sampled from our dataset and removed for subsequent analysis. For all methods, we use OpenAI's ChatGPT (OpenAI, 2022) as the base language model due to its generative capabilities.

No-context LM. We feed language models the prompt `Input: <sentence> Edit:` and ask it to edit the text, without any retrieved context.

Retrv→LM. To assist an editor model, we use a passage retrieval system to find supporting evidence from an external knowledge source (Wikipedia in our case). Our retrieval pipeline is identical to Section B.1, but uses 3 retrieved passages instead of 5 due to context length restrictions.

+ Atomic Facts. Additionally, we explore whether adding atomic facts and their labels assist a model with fine-grained editing. Specifically, after the input sentence we add information to the prompt of the form `Fact 1 (True/False): <atomic fact 1> Fact 2 (True/False): <atomic fact 2>` . . . This data is also provided in the exemplars.

	InstructGPT			ChatGPT			PerplexityAI		
Editor	ErrLoc	ErrCorr	SimAl	ErrLoc	ErrCorr	SimAl	ErrLoc	ErrCorr	SimAl
Input copying	37.1	0.0	0.0	38.8	0.0	0.0	45.6	0.0	0.0
25% random noise	44.1	0.1	0.5	45.5	0.1	0.4	45.2	0.0	0.3
ChatGPT									
No-context	49.0	8.5	6.2	45.3	6.8	4.0	48.3	6.2	4.1
No-context + atomic facts	58.7	12.7	10.5	53.4	10.0	6.6	56.0	9.6	6.1
Retrv→LM	52.6	21.8	15.7	43.9	16.8	9.5	46.3	13.5	6.8
Retrv→LM + atomic facts	**65.4**	**30.4**	**25.5**	**63.5**	**28.3**	**19.3**	**62.4**	**23.6**	**15.9**

Table 14: Results after automatic editing with ChatGPT assuming ground truth verification labels. All editors perform better than trivial lowerbound baselines, and using retrieval and atomic fact labels boosts editing performance. Details of automatic metrics (ErrLoc, ErrCorr, SimAl) are defined in Section C.2.

Non-edit baselines. Finally, we add some trivial baselines to lower-bound our editing metrics. Specifically, we measure the performance of input copying (no edits), as well as an editor with random token dropping / replacement on a random 25% subset of tokens.

C.2 Evaluation

In our data collection process (Section 3.2), along with our verification data we also collected gold-standard human written edits. Let $X = x_1, ...x_{N_X}$ be the input sentence and $G = g_1, ...g_{N_G}$ be the gold edited sentence. We evaluate the quality of the model-generated edit ($E = e_1, ..., e_{N_E}$) using three automatic metrics,

(1) **Error Localization** (ErrLoc): Our first metric measures how well the editor identifies errors within the input sentence. Specifically, we first create a "token preservation string", marking token x_i in the input sentence X as "Preserved" or "Not Preserved". We then compute the macro-averaged F1 score between the token preservation strings derived from the gold edit and the model-generated edit. We remove stopwords, punctuation and lowercase all words before performing this calculation. To equally weigh every sentence, F1 scores are independently computed for each sentence before a final averaging.

(2) **Edit Correctness** (EditCorr): Our second metric assesses the quality of the additional tokens added by the model-generated edit. Specifically, we check the token-level F1 score (Rajpurkar et al., 2016) comparing the new tokens added by the gold edit G and the new tokens added by the model-generated edit E. More concretely,

$$\begin{aligned}
N_{\text{common}} &= \sum_{e_i \in E, e_i \notin X} e_i \in G \\
\text{precision} &= N_{\text{common}} \;/\; ||\{e_i \in E, e_i \notin X\}|| \\
\text{recall} &= N_{\text{common}} \;/\; ||\{g_i \in G, g_i \notin X\}|| \\
\text{EditCorr (F1)} &= \text{HM}(\text{precision}, \text{recall})
\end{aligned}$$

where $|| \cdot ||$ is the set cardinality and HM denotes a harmonic mean. For this metric, we discard data points where the gold edit did not add new tokens. Similar to ErrLoc, we also remove stopwords, remove punctuation and lowercase strings before calculating EditCorr scores.

(3) **SIM alignment** (SimAl): Finally, due to the large output space of possible edits, we also adopt a metric which rewards paraphrases of the gold edits. We use semantic similarity embeddings from Wieting et al. (2022) which map paraphrases to a similar part of a vector space. We check the similarity between the model edit E and the gold edit G, normalizing it by the similarity between G

and the original input X.[19] Specifically,

$$\text{Sim} = \max\left(0, \frac{s(G,E) - s(G,X)}{1 - s(G,X)}\right)$$

where $s(A, B)$ is the semantic similarity score (normalized to $[0, 1]$) from the model in Wieting et al. (2022). Intuitively, this metric measures how much closer G and E are compared to G and X.

C.3 Results

We present our editing results in Table 14. Overall, we find that:

All editing models perform better than trivial lower bounds. Overall, we find that all editor models outperform lower-bound baselines like random noise. This even happens in the no-context LM setting, where ChatGPT is editing its own output (or search engine augmented Perplexity AI's outputs), but can still perform non-trivial corrections (6.8 ErrCorr for ChatGPT correcting its own outputs vs 0.1 for a random noise editor baseline).

Retrieval significantly helps with editing performance. Across all base language models and metrics, augmenting the editor with retrieved paragraphs boosts performance (6.8 → 16.8 ErrCorr, 4.0 → 9.5 SimAl for ChatGPT correcting its own outputs). We hypothesize that the internal parametric knowledge in ChatGPT has insufficient information about the topic (as we also observed in Section 3.3) to perform fine-grained editing, and using external knowledge from Wikipedia greatly simplifies error localization and correction. This also corroborates with our findings in Section 4.2.

Atomic fact labels improve error localization and improve editing performance. Across all base language models (with or without retrieval) we observe that providing fine-grained atomic fact labels improves editing performance (16.8 → 28.3 ErrCorr, 9.5 → 19.3 SimAl for ChatGPT correcting its own outputs). Fine-grained fact correctness labels help the editor easily identify problematic tokens, as seen by the consistent improvements in ErrLoc scores (43.9 → 63.5 for ChatGPT correcting itself). We hypothesize atomic facts help guide the editor with its editing process (for instance, perform a more targeted search in the retrieved paragraphs), resulting in ErrCorr improvements. We also find that atomic fact labels reduces the frequency of editor copying the input verbatim or saying *The input has no errors* from 37.3% to 3.9%.

PerplexityAI outputs are the hardest to edit. Overall, we find the highest editing success for InstructGPT, followed by ChatGPT and the least success for Perplexity AI. We hypothesize this is because PerplexityAI already uses a search engine, so errors are much more subtle as extensively discussed in Appendix A.5.

[19] We avoid taking the vector differences between the original / edited text since edit vectors (Guu et al., 2018) were not explicitly modeled in Wieting et al. (2022).

Table 15: A prompt given to InstructGPT to generate atomic facts for a given sentence. Model generated atomic facts were revised by human editors.

Please breakdown the following sentence into independent facts: He made his acting debut in the film The Moon is the Sun's Dream (1992), and continued to appear in small and supporting roles throughout the 1990s.
- He made his acting debut in the film.
- He made his acting debut in The Moon is the Sun's Dream.
- The Moon is the Sun's Dream is a film.
- The Moon is the Sun's Dream was released in 1992.
- After his acting debut, he appeared in small and supporting roles.
- After his acting debut, he appeared in small and supporting roles throughout the 1990s.

Please breakdown the following sentence into independent facts: He is also a successful producer and engineer, having worked with a wide variety of artists, including Willie Nelson, Tim McGraw, and Taylor Swift.
- He is successful.
- He is a producer.
- He is a engineer.
- He has worked with a wide variety of artists.
- Willie Nelson is an artist.
- He has worked with Willie Nelson.
- Tim McGraw is an artist.
- He has worked with Tim McGraw.
- Taylor Swift is an artist.
- He has worked with Taylor Swift.

Please breakdown the following sentence into independent facts: In 1963, Collins became one of the third group of astronauts selected by NASA and he served as the back-up Command Module Pilot for the Gemini 7 mission.
- Collins became an astronaut.
- Collins became one of the third group of astronauts.
- Collins became one of the third group of astronauts selected.
- Collins became one of the third group of astronauts selected by NASA.
- Collins became one of the third group of astronauts selected by NASA in 1963.
- He served as the Command Module Pilot.
- He served as the back-up Command Module Pilot.
- He served as the Command Module Pilot for the Gemini 7 mission.

Please breakdown the following sentence into independent facts: In addition to his acting roles, Bateman has written and directed two short films and is currently in development on his feature debut.
- Bateman has acting roles.
- Bateman has written two short films.
- Bateman has directed two short films.
- Bateman has written and directed two short films.
- Bateman is currently in development on his feature debut.

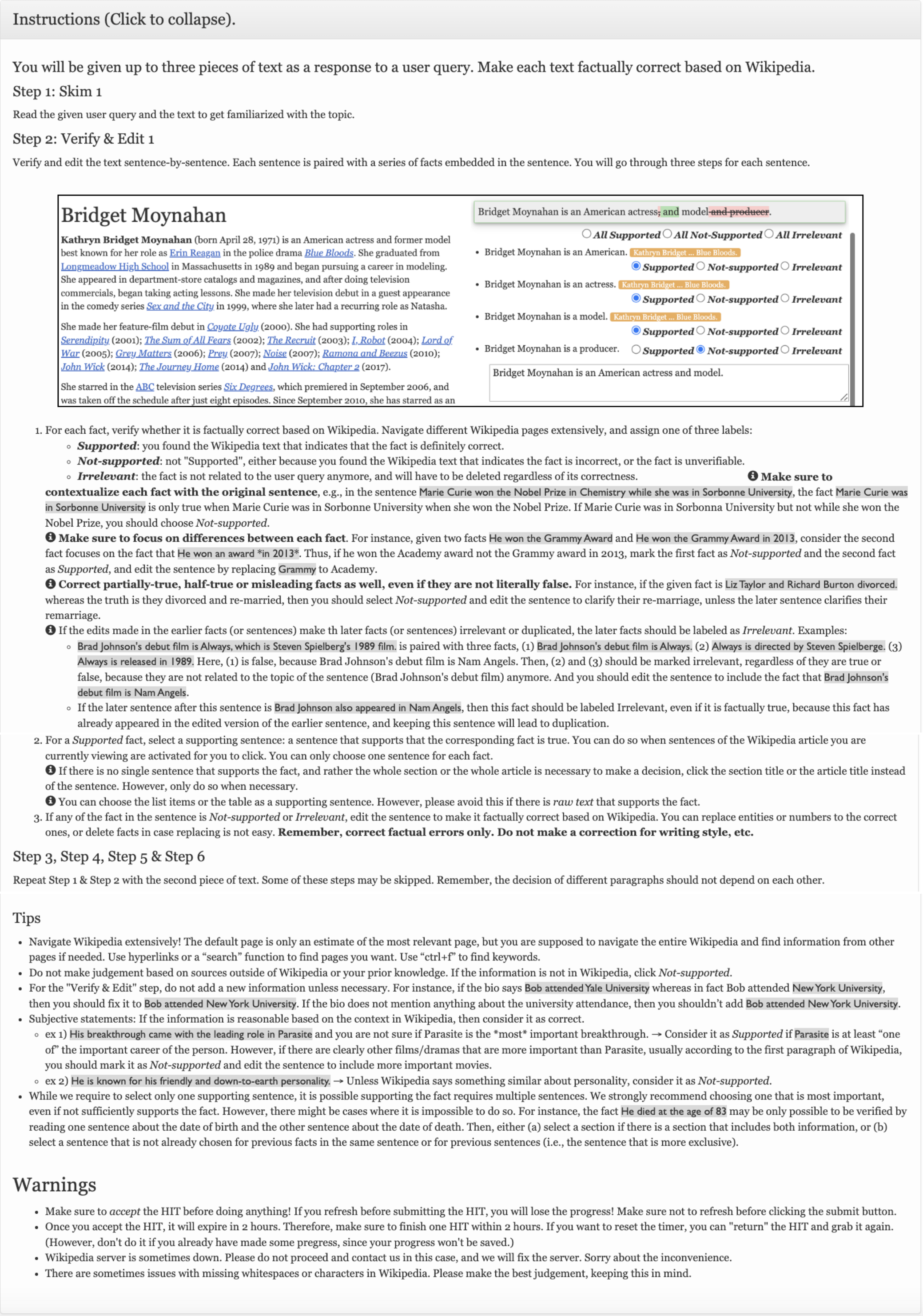
Please breakdown the following sentence into independent facts: Michael Collins (born October 31, 1930) is a retired American astronaut and test pilot who was the Command Module Pilot for the Apollo 11 mission in 1969.
- Michael Collins was born on October 31, 1930.
- Michael Collins is retired.
- Michael Collins is an American.
- Michael Collins was an astronaut.
- Michael Collins was a test pilot.
- Michael Collins was the Command Module Pilot.
- Michael Collins was the Command Module Pilot for the Apollo 11 mission.
- Michael Collins was the Command Module Pilot for the Apollo 11 mission in 1969.

Please breakdown the following sentence into independent facts: He was an American composer, conductor, and musical director.
- He was an American.
- He was a composer.
- He was a conductor.
- He was a musical director.

Please breakdown the following sentence into independent facts: She currently stars in the romantic comedy series, Love and Destiny, which premiered in 2019.
- She currently stars in Love and Destiny.
- Love and Destiny is a romantic comedy series.
- Love and Destiny premiered in 2019.

Please breakdown the following sentence into independent facts: During his professional career, McCoy played for the Broncos, the San Diego Chargers, the Minnesota Vikings, and the Jacksonville Jaguars.
- McCoy played for the Broncos.
- McCoy played for the Broncos during his professional career.
- McCoy played for the San Diego Chargers.
- McCoy played for the San Diego Chargers during his professional career.
- McCoy played for the Minnesota Vikings.
- McCoy played for the Minnesota Vikings during his professional career.
- McCoy played for the Jacksonville Jaguars.
- McCoy played for the Jacksonville Jaguars during his professional career.

Please breakdown the following sentence into independent facts



Instructions (Click to collapse).

You will be given up to three pieces of text as a response to a user query. Make each text factually correct based on Wikipedia.

Step 1: Skim 1

Read the given user query and the text to get familiarized with the topic.

Step 2: Verify & Edit 1

Verify and edit the text sentence-by-sentence. Each sentence is paired with a series of facts embedded in the sentence. You will go through three steps for each sentence.

Bridget Moynahan

Kathryn Bridget Moynahan (born April 28, 1971) is an American actress and former model best known for her role as Erin Reagan in the police drama *Blue Bloods*. She graduated from Longmeadow High School in Massachusetts in 1989 and began pursuing a career in modeling. She appeared in department-store catalogs and magazines, and after doing television commercials, began taking acting lessons. She made her television debut in a guest appearance in the comedy series *Sex and the City* in 1999, where she later had a recurring role as Natasha.

She made her feature-film debut in *Coyote Ugly* (2000). She had supporting roles in *Serendipity* (2001); *The Sum of All Fears* (2002); *The Recruit* (2003); *I, Robot* (2004); *Lord of War* (2005); *Grey Matters* (2006); *Prey* (2007); *Noise* (2007); *Ramona and Beezus* (2010); *John Wick* (2014); *The Journey Home* (2014) and *John Wick: Chapter 2* (2017).

She starred in the ABC television series *Six Degrees*, which premiered in September 2006, and was taken off the schedule after just eight episodes. Since September 2010, she has starred as an

Bridget Moynahan is an American actress~~,~~ and model~~ and producer~~.

○ ***All Supported*** ○ ***All Not-Supported*** ○ ***All Irrelevant***

- Bridget Moynahan is an American. Kathryn Bridget ... Blue Bloods.
  ● ***Supported*** ○ ***Not-supported*** ○ ***Irrelevant***
- Bridget Moynahan is an actress. Kathryn Bridget ... Blue Bloods.
  ● ***Supported*** ○ ***Not-supported*** ○ ***Irrelevant***
- Bridget Moynahan is a model. Kathryn Bridget ... Blue Bloods.
  ● ***Supported*** ○ ***Not-supported*** ○ ***Irrelevant***
- Bridget Moynahan is a producer. ○ ***Supported*** ● ***Not-supported*** ○ ***Irrelevant***

Bridget Moynahan is an American actress and model.

1. For each fact, verify whether it is factually correct based on Wikipedia. Navigate different Wikipedia pages extensively, and assign one of three labels:
   - ***Supported***: you found the Wikipedia text that indicates that the fact is definitely correct.
   - ***Not-supported***: not "Supported", either because you found the Wikipedia text that indicates the fact is incorrect, or the fact is unverifiable.
   - ***Irrelevant***: the fact is not related to the user query anymore, and will have to be deleted regardless of its correctness.

   ℹ **Make sure to contextualize each fact with the original sentence**, e.g., in the sentence Marie Curie won the Nobel Prize in Chemistry while she was in Sorbonne University, the fact Marie Curie was in Sorbonne University is only true when Marie Curie was in Sorbonne University when she won the Nobel Prize. If Marie Curie was in Sorbonna University but not while she won the Nobel Prize, you should choose *Not-supported*.

   ℹ **Make sure to focus on differences between each fact**. For instance, given two facts He won the Grammy Award and He won the Grammy Award in 2013, consider the second fact focuses on the fact that He won an award *in 2013*. Thus, if he won the Academy award not the Grammy award in 2013, mark the first fact as *Not-supported* and the second fact as *Supported*, and edit the sentence by replacing Grammy to Academy.

   ℹ **Correct partially-true, half-true or misleading facts as well, even if they are not literally false.** For instance, if the given fact is Liz Taylor and Richard Burton divorced. whereas the truth is they divorced and re-married, then you should select *Not-supported* and edit the sentence to clarify their re-marriage, unless the later sentence clarifies their remarriage.

   ℹ If the edits made in the earlier facts (or sentences) make th later facts (or sentences) irrelevant or duplicated, the later facts should be labeled as *Irrelevant*. Examples:
   - Brad Johnson's debut film is Always, which is Steven Spielberg's 1989 film. is paired with three facts, (1) Brad Johnson's debut film is Always. (2) Always is directed by Steven Spielberge. (3) Always is released in 1989. Here, (1) is false, because Brad Johnson's debut film is Nam Angels. Then, (2) and (3) should be marked irrelevant, regardless of they are true or false, because they are not related to the topic of the sentence (Brad Johnson's debut film) anymore. And you should edit the sentence to include the fact that Brad Johnson's debut film is Nam Angels.
   - If the later sentence after this sentence is Brad Johnson also appeared in Nam Angels, then this fact should be labeled Irrelevant, even if it is factually true, because this fact has already appeared in the edited version of the earlier sentence, and keeping this sentence will lead to duplication.
2. For a *Supported* fact, select a supporting sentence: a sentence that supports that the corresponding fact is true. You can do so when sentences of the Wikipedia article you are currently viewing are activated for you to click. You can only choose one sentence for each fact.

   ℹ If there is no single sentence that supports the fact, and rather the whole section or the whole article is necessary to make a decision, click the section title or the article title instead of the sentence. However, only do so when necessary.

   ℹ You can choose the list items or the table as a supporting sentence. However, please avoid this if there is *raw text* that supports the fact.
3. If any of the fact in the sentence is *Not-supported* or *Irrelevant*, edit the sentence to make it factually correct based on Wikipedia. You can replace entities or numbers to the correct ones, or delete facts in case replacing is not easy. **Remember, correct factual errors only. Do not make a correction for writing style, etc.**

Step 3, Step 4, Step 5 & Step 6

Repeat Step 1 & Step 2 with the second piece of text. Some of these steps may be skipped. Remember, the decision of different paragraphs should not depend on each other.

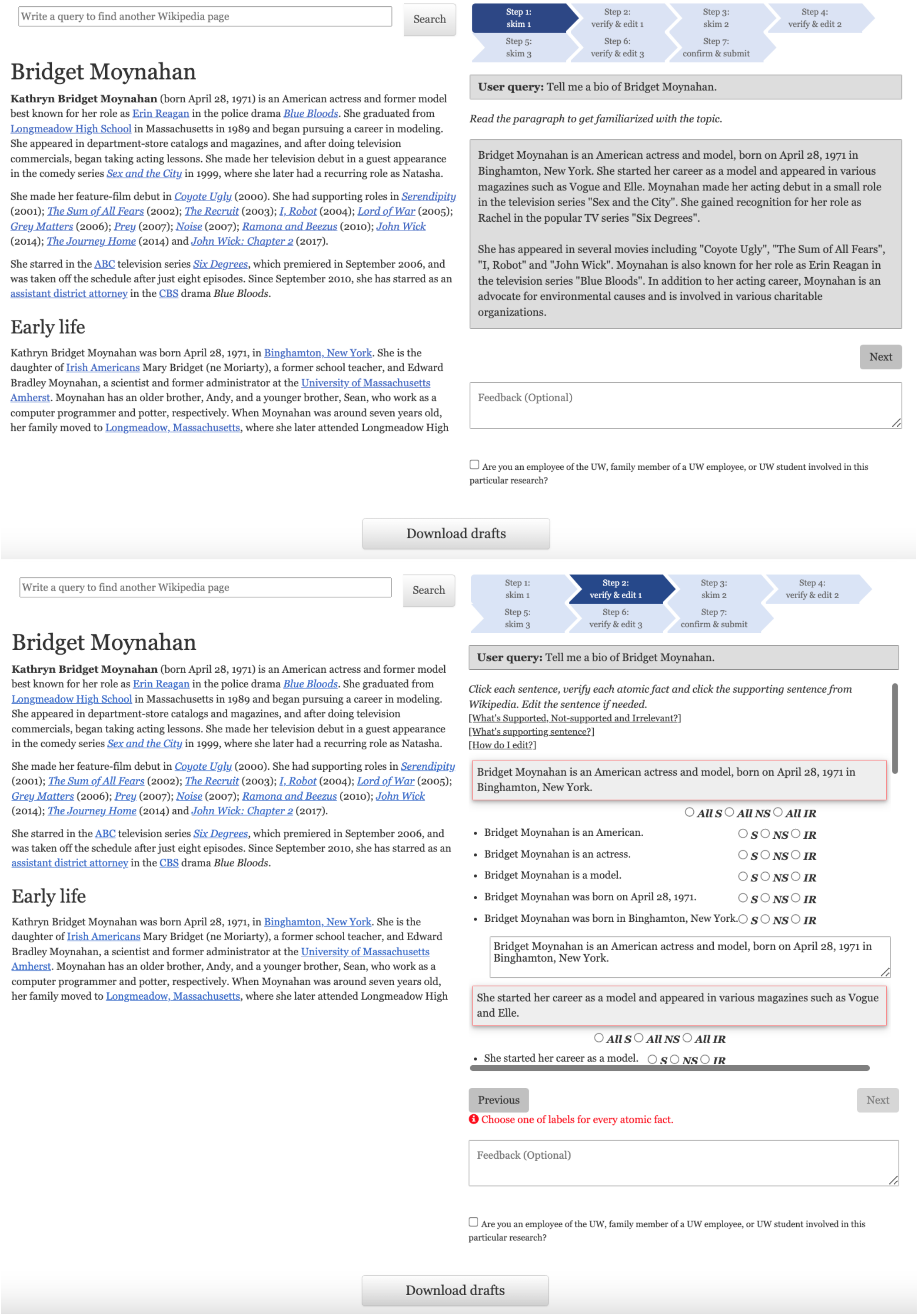
Tips

- Navigate Wikipedia extensively! The default page is only an estimate of the most relevant page, but you are supposed to navigate the entire Wikipedia and find information from other pages if needed. Use hyperlinks or a "search" function to find pages you want. Use "ctrl+f" to find keywords.
- Do not make judgement based on sources outside of Wikipedia or your prior knowledge. If the information is not in Wikipedia, click *Not-supported*.
- For the "Verify & Edit" step, do not add a new information unless necessary. For instance, if the bio says Bob attended Yale University whereas in fact Bob attended New York University, then you should fix it to Bob attended New York University. If the bio does not mention anything about the university attendance, then you shouldn't add Bob attended New York University.
- Subjective statements: If the information is reasonable based on the context in Wikipedia, then consider it as correct.
  - ex 1) His breakthrough came with the leading role in Parasite and you are not sure if Parasite is the *most* important breakthrough. → Consider it as *Supported* if Parasite is at least "one of" the important career of the person. However, if there are clearly other films/dramas that are more important than Parasite, usually according to the first paragraph of Wikipedia, you should mark it as *Not-supported* and edit the sentence to include more important movies.
  - ex 2) He is known for his friendly and down-to-earth personality. → Unless Wikipedia says something similar about personality, consider it as *Not-supported*.
- While we require to select only one supporting sentence, it is possible supporting the fact requires multiple sentences. We strongly recommend choosing one that is most important, even if not sufficiently supports the fact. However, there might be cases where it is impossible to do so. For instance, the fact He died at the age of 83 may be only possible to be verified by reading one sentence about the date of birth and the other sentence about the date of death. Then, either (a) select a section if there is a section that includes both information, or (b) select a sentence that is not already chosen for previous facts in the same sentence or for previous sentences (i.e., the sentence that is more exclusive).

Warnings

- Make sure to *accept* the HIT before doing anything! If you refresh before submitting the HIT, you will lose the progress! Make sure not to refresh before clicking the submit button.
- Once you accept the HIT, it will expire in 2 hours. Therefore, make sure to finish one HIT within 2 hours. If you want to reset the timer, you can "return" the HIT and grab it again. (However, don't do it if you already have made some pregress, since your progress won't be saved.)
- Wikipedia server is sometimes down. Please do not proceed and contact us in this case, and we will fix the server. Sorry about the inconvenience.
- There are sometimes issues with missing whitespaces or characters in Wikipedia. Please make the best judgement, keeping this in mind.

Figure 6: Instructions for data annotation in Section 4. We also provided a demonstration video, and gave feedback 1-1 during the qualification task.



Bridget Moynahan

Kathryn Bridget Moynahan (born April 28, 1971) is an American actress and former model best known for her role as Erin Reagan in the police drama *Blue Bloods*. She graduated from Longmeadow High School in Massachusetts in 1989 and began pursuing a career in modeling. She appeared in department-store catalogs and magazines, and after doing television commercials, began taking acting lessons. She made her television debut in a guest appearance in the comedy series *Sex and the City* in 1999, where she later had a recurring role as Natasha.

She made her feature-film debut in *Coyote Ugly* (2000). She had supporting roles in *Serendipity* (2001); *The Sum of All Fears* (2002); *The Recruit* (2003); *I, Robot* (2004); *Lord of War* (2005); *Grey Matters* (2006); *Prey* (2007); *Noise* (2007); *Ramona and Beezus* (2010); *John Wick* (2014); *The Journey Home* (2014) and *John Wick: Chapter 2* (2017).

She starred in the ABC television series *Six Degrees*, which premiered in September 2006, and was taken off the schedule after just eight episodes. Since September 2010, she has starred as an assistant district attorney in the CBS drama *Blue Bloods*.

Early life

Kathryn Bridget Moynahan was born April 28, 1971, in Binghamton, New York. She is the daughter of Irish Americans Mary Bridget (ne Moriarty), a former school teacher, and Edward Bradley Moynahan, a scientist and former administrator at the University of Massachusetts Amherst. Moynahan has an older brother, Andy, and a younger brother, Sean, who work as a computer programmer and potter, respectively. When Moynahan was around seven years old, her family moved to Longmeadow, Massachusetts, where she later attended Longmeadow High

User query: Tell me a bio of Bridget Moynahan.

Read the paragraph to get familiarized with the topic.

Bridget Moynahan is an American actress and model, born on April 28, 1971 in Binghamton, New York. She started her career as a model and appeared in various magazines such as Vogue and Elle. Moynahan made her acting debut in a small role in the television series "Sex and the City". She gained recognition for her role as Rachel in the popular TV series "Six Degrees".

She has appeared in several movies including "Coyote Ugly", "The Sum of All Fears", "I, Robot" and "John Wick". Moynahan is also known for her role as Erin Reagan in the television series "Blue Bloods". In addition to her acting career, Moynahan is an advocate for environmental causes and is involved in various charitable organizations.

□ Are you an employee of the UW, family member of a UW employee, or UW student involved in this particular research?

Bridget Moynahan

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User query: Tell me a bio of Bridget Moynahan.

Click each sentence, verify each atomic fact and click the supporting sentence from Wikipedia. Edit the sentence if needed.
[What's Supported, Not-supported and Irrelevant?]
[What's supporting sentence?]
[How do I edit?]

Bridget Moynahan is an American actress and model, born on April 28, 1971 in Binghamton, New York.

○ ***All S*** ○ ***All NS*** ○ ***All IR***

- Bridget Moynahan is an American. ○ ***S*** ○ ***NS*** ○ ***IR***
- Bridget Moynahan is an actress. ○ ***S*** ○ ***NS*** ○ ***IR***
- Bridget Moynahan is a model. ○ ***S*** ○ ***NS*** ○ ***IR***
- Bridget Moynahan was born on April 28, 1971. ○ ***S*** ○ ***NS*** ○ ***IR***
- Bridget Moynahan was born in Binghamton, New York.○ ***S*** ○ ***NS*** ○ ***IR***

Bridget Moynahan is an American actress and model, born on April 28, 1971 in Binghamton, New York.

She started her career as a model and appeared in various magazines such as Vogue and Elle.

○ ***All S*** ○ ***All NS*** ○ ***All IR***

- She started her career as a model. ○ ***S*** ○ ***NS*** ○ ***IR***

Choose one of labels for every atomic fact.

□ Are you an employee of the UW, family member of a UW employee, or UW student involved in this particular research?

Figure 7: An interface for data annotation in Section 4. Annotators were able to navigate Wikipedia on the left. They annotate three pieces of generations from three LMs for the same prompt in one HIT since it saves time. Since completing one HIT takes considerable amount of time (25min), we added a function that allows saving their work at any stage in the middle of the HIT.