Real-time Fake News from Adversarial Feedback

Anonymous ACL submission

Abstract

We show that existing evaluations for fake news detection based on conventional sources, such as claims on fact-checking websites, result in an increasing accuracy over time for LLM-based detectors—even after their knowledge cutoffs. This suggests that recent popular political claims, which form the majority of fake news on such sources, are easily classified using surface-level shallow patterns. Instead, we argue that a proper fake news detection dataset should test a model's ability to reason factually about the current world by retrieving and reading related evidence. To this end, we develop a novel pipeline that leverages natural language feedback from a RAG-based detector to iteratively modify real-time news into deceptive fake news that challenges LLMs. Our iterative rewrite decreases the binary classification AUC by an absolute 17.5 percent for a strong RAG GPT-4o detector. Our experiments reveal the important role of RAG in both detecting and generating fake news, as retrieval-free LLM detectors are vulnerable to unseen events and adversarial attacks, while feedback from RAG detection helps discover more deceitful patterns in fake news.

1 Introduction

Disinformation and fake news have emerged as major societal concerns. The spread of fake news can cause serious consequences, such as influencing elections, inciting violence, and misleading critical decision-making, especially in health. In the NLP community, researchers have long focused on developing methods and evaluation for automatic fake news detection (Zellers et al., 2019). The rise of LLMs has significantly changed the landscape of this problem (Goldstein et al., 2023; Chen and Shu, 2023).

LLMs have demonstrated impressive knowledge and reasoning ability. They can generate fake news that is more deceitful than human-written news, and they can detect fake news with high accuracy (Chen and Shu, 2024; Pelrine et al., 2023). The pre-training and prompting paradigm of LLMs reduces the risk of creating dataset-specific models that are prone to in-distribution shortcut learning (Pagnoni et al., 2022). However, due to the opaque nature of LLM training, their evaluation is often influenced by potential contamination issues, which can result in misleading outcomes and a need for out-of-distribution evaluation (Zhou et al., 2023; Vu et al., 2024; Huang et al., 2024). Existing fake news detection datasets are commonly sourced from past claims from fact-checking websites (Wang, 2017; Shu et al., 2018). These websites, such as PolitiFact and Snopes, often feature popular claims from politicians that are widely circulated on the internet, leading to potential contamination during the large-scale pre-training of LLMs.

Collecting new data from fact-checking websites does not address this issue. Recent research has reported that LLMs (e.g., GPT-4) remain effective in detecting fake news that falls outside their knowledge cutoffs (Pelrine et al., 2023). We conduct the first comprehensive analysis of retrieval-free LLM detectors on PolitiFact data over the years, revealing a surprising upward trend in detection performance (Figure 1). The trend continues to rise even after the knowledge cutoff dates of models, suggesting a gain from *non-factual* salient patterns of recent political claims rather than from increased model knowledge or reasoning ability. In practice, this affects the continued applicability of datasets sourced from political fact-checking for evaluating LLM-based detectors on factual reasoning. As the field evolves toward evidence-based detection, LLMs should rely on retrieval results to examine claims with up-to-date information (Yang et al., 2022; Hu et al., 2023b; Liao et al., 2023). The fact that LLMs can detect most fake news without retrieval augmentation under this evaluation

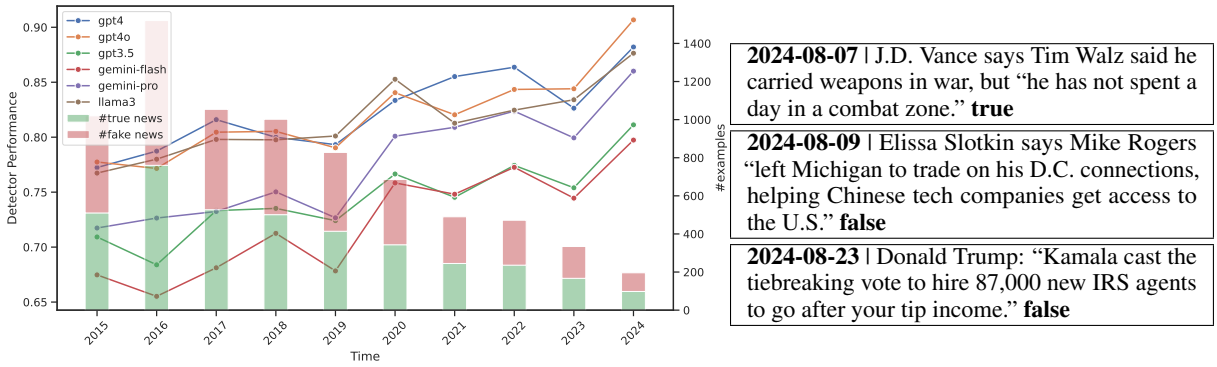

Figure 1: Comparison of different retrieval-free detectors (AUC-ROC) on PolitiFact claims over the years, up to August 2024. The data is balanced by downsampling the majority class. The knowledge cutoffs for each model are gpt-4-turbo-2024-04-09 (Dec 2023), gpt-4o-2024-05-13 (Oct 2023), and gpt-3.5-turbo-0125 (Sep 2021). Gemini models (gemini-1.5-pro-002, gemini-1.5-flash-002) have a knowledge cutoff of November 2023. Llama 3.1 (405B Instruct) knowledge is up to December 2023. Some 2024 examples are shown on the right.

setup motivates us to explore new ways to create fake news datasets that can better evaluate retrieval-augmented (RAG) detectors.

Inspired by LLMs' ability of continual improvement based on feedback (Madaan et al., 2023), we propose an adversarial iterative approach to generate fake news that can deceive strong LLM-based detectors. The generator leverages feedback from an adversary detector in the form of a rationale discussing the factuality of the machine-generated fake news, mimicking the real-world scenario in which fact-checkers provide explanations for their verdicts. Given this verdict and the fake news generated in the previous round, the generator then adds another round of modifications to the fake news such that it would fool the prior verdict. This process is repeated a few times, allowing the generator to learn from the detector's perspective. Empirically, highly performant LLM-based detectors on conventional political fact-checking struggle with the fake news generated by our approach.

Our approach emphasizes the importance of retrieval-augmentation in both the generation and detection of fake news. First, we source real-time news articles from various domains, which are beyond the knowledge of LLMs and necessitate retrieval for fact-checking. Second, we show that RAG-based detection with up-to-date external knowledge is a strong defense against machine-generated fake news. Lastly, we demonstrate that the iterative adversarial process creates fake news with increasing deception that generalizes well across different setups that vary in LLM backbones and retrieval contexts, while being more effective when utilizing feedback from a RAG-based detector.[1]

2 Background

2.1 Problem Formulation

We formulate the fake news detection task as a binary classification problem, where the primary objective is to determine whether a given news article is genuine or fabricated. Let $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^{N}$ represent the dataset, where each x_i is a news article and $y_i \in \{0, 1\}$ is a binary label indicating the authenticity of the article. A detector $f : \mathcal{X} \rightarrow [0, 1]$ maps each news article x_i to a probabilistic score $\hat{y}_i = f(x_i)$, reflecting the likelihood of the article being true news. The effectiveness of a detector is evaluated using the Area Under the Receiver Operating Characteristic Curve (AUC-ROC), which quantifies the model's capability to classify across various threshold settings.

2.2 Analysis of Political Fake News Detection

Popular fake news detection datasets, such as LIAR (Wang, 2017) and FakeNewsNet (Shu et al., 2018), obtain news content and human labels from fact-checking websites like PolitiFact.[2] Depending on the time of data collection, the datasets consist of claims ranging from 2007-2018, which are within the knowledge cutoff of most LLMs available today. In order to evaluate the performance of LLM-based detectors on recent year data, we collect all 15171 PolitiFact claims from June, 2015 to August, 2024. We filter out anonymous social media posts that PolitiFact has widely fact-checked

[1] We will release our code and data to facilitate further research on fake news detection and generation.

[2] https://www.politifact.com/

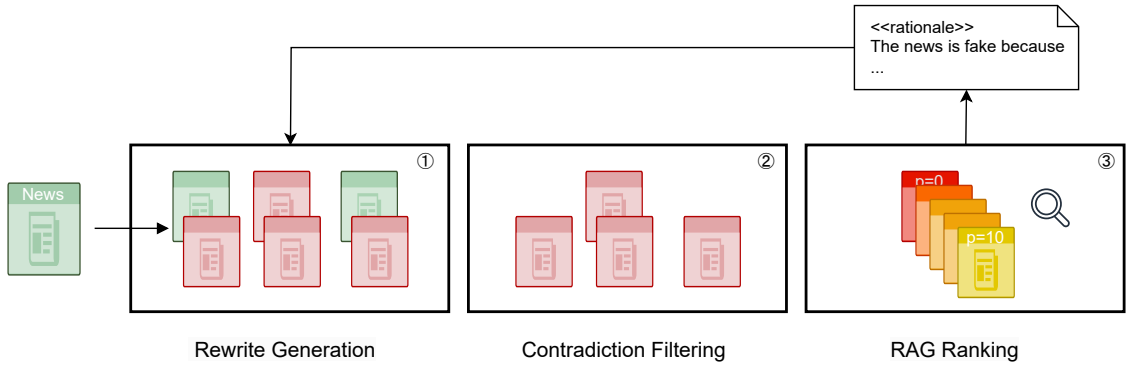

Figure 2: Our proposed adversarial iterative fake news generation. 1) A true news article is rewritten by a LLM to multiple candidates containing misinformation. 2) Candidates that do not contradict the original true news are filtered out. 3) The remaining candidates are ranked on their plausibility score according to a RAG-based detector and the most plausible one is selected, the detector's rationales are used to inform the next round generation. The process can be repeated for multiple iterations.

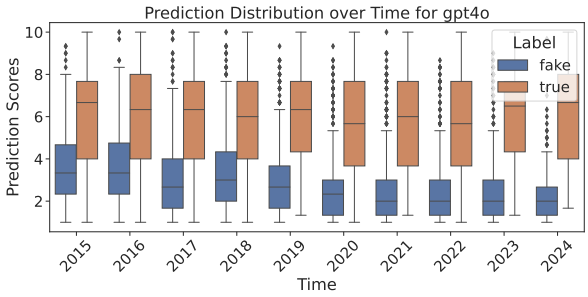

Figure 3: GPT-4o (retrieval-free) predicted plausibility of PolitiFact claims over the years, up to August 2024. The data is balanced by downsampling the majority class. The distribution of the true news class remains relatively stable, while the distribution of the fake news class shifts significantly towards lower scores (indicating more accurate classification).

in recent years, but unfortunately, they are predominantly false. The remaining 9244 claims are mostly from politicians and public figures.

We run a set of retrieval-free LLM-based detectors using the setup described in section 4. We observe that the performance of GPT-based detectors improves over time. In the most recent year, 2024, we see that LLMs continue to improve, even after the knowledge cutoff (and also the model release dates). This suggests that, for state-of-the-art LLMs, up-to-date knowledge is not the deciding factor for political fake news detection performance. Instead, they rely on certain patterns that have emerged over the recent years to fact-check claims. We verify this trend by fine-tuning a relatively small LM, RoBERTa (Liu et al., 2019), on two sets of data from different years. In one experiment, we train the model on PolitiFact data from 2015 and evaluate it on data from 2016. In the other, we train the model on data from 2022 and evaluate it on data from 2023 and 2024. The results show that the later data results in a higher AUC-ROC score (0.765 versus 0.680), which is roughly equal to the performance of the GPT-3.5 detector.

We ablate key features of the detectors such as the originator and time of the claim, and paraphrase the claim content. None of these features affects the trend of increasing performance over the years (Figure 9). The prediction distribution (Figure 3) reveals that the changes are mostly in the detector's perception of the fake news class, which shifts towards lower scores. Manually going through some fake news examples, we find that in earlier years, political fake news contains statements that, while hyperbolic, can be anchored in a context that requires research through reliable sources (e.g., public records or legislative history) to verify. In contrast, recent fake news includes more sensational and less easily verified claims that seem more speculative or exaggerated without immediate substantive evidence. Consequently, the detection of recent fake news requires less factual knowledge and reasoning, but more pattern recognition and common sense.

Additionally, there is a meaningful distribution shift in PolitiFact data over the years. We observe that the proportion and the absolute number of true news has decreased significantly in recent years, which may result from the increasing prevalence of misinformation in the political landscape (see Figure 8 for unbalanced data distribution). From a

machine learning perspective, this distribution shift leads to pronounced class imbalance, which can negatively impact the evaluation of fake news detection models if not properly accounted for. Lastly, as the AUC-ROC scores of retrieval-free detectors rise above 0.9, the PolitiFact data becomes practically less useful for evaluating the performance of LLM-based detectors, which encourages us to explore new ways to create datasets that cover real-time information from diverse domains for more challenging evaluation.

Algorithm 1 Adversarial Iterative News Rewriting

Require: $TrueNews$, k {k is the maximum number of iterations}
$CurrentFake \leftarrow TrueNews$
for $i \leftarrow 1$ **to** k **do**
  $Candidates \leftarrow$ GenerateCandidates($CurrentFake$)
  repeat
    $Filtered \leftarrow \emptyset$
    for each c_i **in** $Candidates$ **do**
      if ContradictsOriginal(c_i, $TrueNews$) **and** IsWithinEditLimit(c_i, $TrueNews$) **then**
        $Filtered \leftarrow Filtered \cup \{c_i\}$
      end if
    end for
    if $Filtered = \emptyset$ **then**
      $Candidates \leftarrow$ GenerateCandidates($CurrentFake$)
    end if
  until $Filtered \neq \emptyset$
  $Ranked \leftarrow$ RankByPlausibility($Filtered$)
  $CurrentFake \leftarrow$ SelectMostPlausible($Ranked$)
end for
return $CurrentFake$

3 Methodology

The wide accessibility of LLMs has not only enabled strong detection models but also facilitated the mass generation of more credible and persuasive fake news (Kreps et al., 2022; Goldstein et al., 2023). Therefore, in combating these emerging threats, the evaluation of detection models should also evolve to incorporate challenging machine-generated misinformation.

One key challenge in creating fake news datasets is obtaining automatic labels for the data. Open-ended generation, although effective in creating diverse fake news, simultaneously introduces false positives that are hard to verify due to the professional skills required for fact-checking. Our proposed approach leverages the strengths of LLMs in controlled misinformation generation (Zellers et al., 2019; Chen and Shu, 2024) to manipulate true news articles and introduce factual errors, while maintaining the overall context and style of the original news. We implement filtering protocols as an additional safeguard to reduce invalid generation.

Figure 2 illustrates our pipeline. Formally, we start with a true news corpus $\mathcal{T}$, which contains real-time news articles from various domains. Each news article consists of a headline, a body text, and a publication date. We independently rewrite each news article $\tau_i \in \mathcal{T}$ to generate multiple fake news candidates $\mathcal{F}_i$. To ensure that $\mathcal{F}_i$ contradict the original true news τ_i, we employ a LLM-based contradiction detector. We put an additional upper limit on the amount of edits allowed in the rewriting process using a threshold on the Levenshtein distance $\Delta(\tau_i, f_{ij})$, where $f_{ij} \in \mathcal{F}_i$, between the original true news τ_i and the rewritten news f_{ij}.

After filtering out the candidates that do not meet these criteria, we rank the remaining candidates based on the plausibility score provided by a fake news detector $g(f_{ij}|c)$, where c is the optional external context retrieved by a retrieval model $\mathcal{R}(f_{ij})$. If none of the candidates meet the criteria, the generator resamples a new batch of candidates. From this ranked list, we select the top-ranked candidate as the most plausible fake news article.

$$\hat{f}_i = \arg\max_{f_{ij} \in \mathcal{F}_i} g(f_{ij}|c) \tag{1}$$

$\hat{f}_i$ and the detector's rationale are then serve as additional information to inform the next round of generation on τ_i, creating an iterative process that gradually deceives the detector. In the end of the process, we obtain the most deceptive fake news $\hat{f}_i$ across all iterations.

A critical component of our approach is the retrieval-augmented detector. Using a retrieval-free detector as an adversary, the generator can only improve the factual consistency within the news content or exploit the weaknesses of a LLM with outdated internal knowledge, which can generally be seen as a case of self-evaluation (Kadavath et al., 2022). However, with the information from the retrieved external context, the generator can learn to deceive cross-verification and improve factual

consistency beyond its own knowledge, which is important for our real-time news rewrite setup.

One implementation challenge in Equation 1 is that we need to run retrieval for each candidate to obtain the external context. This can be computationally expensive for sophisticated retrieval models and costly if commercial APIs are used. In practice, we retrieve the external context only for the top-ranked candidates at the end of each iteration, which we use to inform the next round of detection. Because of the constraints on the amount of change in each iteration, the external context is expected to remain relevant for the next batch generation. In final evaluation, we rerun the retrieval each time to ensure the external context is up-to-date.

Method	LIAR		
	AUC	F1-Ma	Acc
RoBERTa-L (2023)	-	64.7	64.1
GPT-4 (2023)	-	68.1	68.2
MUSER (2023)	-	64.5	-
STEEL (2024)	-	71.4	-
GPT-4o	77.5	70.7	70.9
GPT-4o + Google	81.1	74.7	75.6

Table 1: Our GPT-4o detectors demonstrate comparable performance on the LIAR dataset (Wang, 2017) to the state of the art. MUSER and STEEL have access to multi-step retrieval on Wikipedia and Bing, respectively.

4 Experimental Setup

4.1 Data Collection

For the true news corpus, we obtain 431 actual news stories from NBC News[3] using the newsplease crawler (Hamborg et al., 2017). These news stories are from March 1 to March 13, 2024, covering domains such as politics, business, sports, U.S., and world news. We filter out advertisements and other non-news content. The date range is chosen to be beyond the knowledge cutoff of the latest LLMs, thus ensuring no contamination from the training data. This set of news stories serve as seed true news for our generation pipeline and as positive examples for evaluating the detectors. We manually examine the final rewrite and filter out 29 fake news generation that turn out to be true. Comparing 100 examples from the first and last round of rewrites, the noisy ratio remains similar.

To build an in-house RAG pipeline, we gather 811,000 news articles from various news sources within the same date range to create our retrieval corpus. We remove the exact seed true news from the retrieval corpus to avoid direct contamination. For popular news stories, multiple news portals may have similar coverage, which we allow for cross-verification. They still contain varying details that the detector can reason about (Table 6). A dense passage retriever (Karpukhin et al., 2020) pretrained on the Natural Questions dataset (Kwiatkowski et al., 2019) is employed to index this corpus and provide 5 relevant articles when queried with a news headline. We additionally implement an online RAG pipeline using SerpApi[4] to retrieve 5 Google search snippets for the given news headlines. We remove NBC News from the search results for similar reasons stated above. Due to the cost of the API, we only use it for the final evaluation of the generated fake news.

4.2 Generator Setup

We adopt GPT-4o as the main LLM for the generation pipeline. The pipeline is iterated for 6 rounds with an extra preparation round 0 of a direct rewrite (no rationale and ranking) on the seed true news. We instruct the LLM to "*introduce some believable factual errors*" without mentioning any concrete strategies or constraints, leaving the candidate generation process open-ended. The generator produces 8 candidates in a zero-shot chain-of-thought fashion for each news story in each round, which are then filtered and ranked based on the plausibility score from the detector. The contradiction detector produces 10 binary scores for each candidate, only if more than eight of them are positive, the candidate is considered to contradict the original true news. String edit distance is used to limit the amount of change in each iteration, with a threshold of more than 60% overlapped tokens.

4.3 Detector Setup

For implementing the LLM detectors, we simply instruct the models to produce plausibility scores (1-10) for the given news story in a zero-shot setting. We use the directive "*Today is March 26, 2024. You predict the plausibility of a news you haven't seen*" to inform the model about the current date and the unseen nature of the news story. The detector generates multiple plausibility scores for each news story using temperature $t = 1$, which we average to obtain the final score. Our GPT-4o de-

[3] https://www.nbcnews.com

[4] https://serpapi.com

Retriever	None			News			Google		
Detector	first	last	Δ	first	last	Δ	first	last	Δ
Gemini-Flash	57.0	50.7	6.3	76.1	62.4	13.8	84.1	76.6	7.5
Gemini-Pro	58.6	51.6	7.0	74.9	62.8	12.1	82.6	73.7	8.9
GPT-3.5	53.7	50.3	3.4	69.3	57.6	11.7	78.2	69.3	8.9
GPT-4o	58.5	48.8	9.7	82.4	64.9	17.5	93.1	86.1	7.0
Llama 3.1	60.5	54.0	6.6	81.3	67.4	13.9	93.3	86.6	6.7

Table 2: AUC-ROC scores of different detectors on the generated fake news of the first and last iteration. The Δ column shows the effects of the iterative process. *News* refers to the in-house DPR retriever on news-please data, and *Google* refers to the Google search API results. The theoretical AUC for a random classifier on this balanced dataset is 50%.

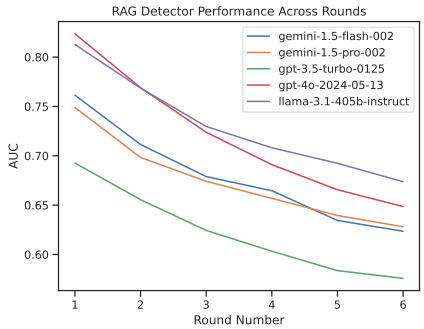

Figure 4: RAG-based detectors with different LLM backbones (AUC-ROC) on iteratively generated fake news. Our pipeline generates fake news that can not only fool GPT-4o, which is used for generation, but also other LLMs. More iterations generally lead to stronger deception.

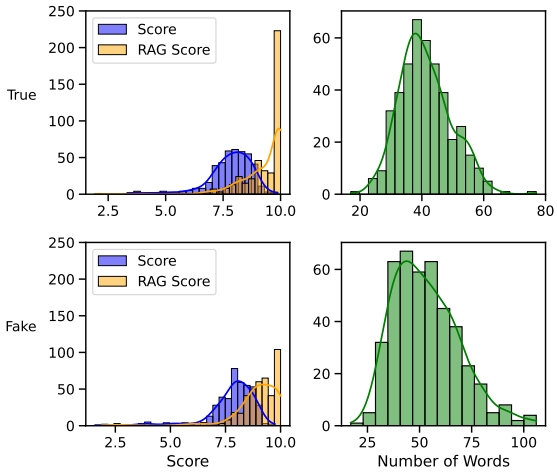

Figure 5: Distribution of the plausibility scores (retrieval-free and RAG) and the number of words in the true news articles from NBC News (positives, top) and the last-round rewritten fake news (negatives, bottom).

tector is comparable to recent state-of-the-art RAG detectors on the popular LIAR datasets (Table 1). We do not adopt chain-of-thought prompting based on indifferent benchmarking results. The detector generate the rationale in a separate LLM call.

We evaluate the generated fake news on different LLM detectors, including GPT-4, GPT-3.5, Gemini Pro and Flash (Gemini Team, 2024), and open-source 405B Llama 3.1 (Meta AI, 2024). Detailed versions and knowledge cutoffs are provided in Figure 1. The actual prompts used by all components are provided in Appendix A.2.

5 Experimental Results

Evaluation results are presented in Table 2 and Figure 4. These results show that our adversarial iterative generation pipeline can produce fake news that can deceive strong LLM-based detectors. We find the Llama 3.1 model to be the best at detecting fake news generated by our pipeline using GPT-4o, especially for later iterations. As the earliest released model in our selection, GPT-3.5 is the most vulnerable, consistent with results of well-established public benchmarks (Chiang et al., 2024).

Through each iteration, the pipeline progressively enhances the deceptive quality of the generated fake news. Relying on the feedback from the GPT-4o RAG-based detector with the in-house retrieval corpus, the generator proves most effective at deceiving this particular detection setting, achieving a reduction of 17.5 AUC-ROC points. Nevertheless, these enhancements are shown to consistently generalize across different LLM backbones and retrieval contexts.

5.1 Analysis

Real-time news can be implausible to off-the-shelf LLM detectors. We find that the true news

1. *Trump says he will debate Biden anytime*

After skipping On March 6, 2024, after participating in a few select GOP primary debates, Trump challenged Biden to step onto a stage with him before the November election. , suggesting that the debate be held at a neutral venue yet to be decided.

2. *Violence, hunger Rising violence, growing food shortages, and unstable missing political leadership*
A long-simmering severe crisis in Haiti has come to a head reached alarming levels as its leader remains stranded in Puerto Rico while its people starve the Dominican Republic for several days. Citizens face extreme food shortages and live in fear of rampant escalating gang-related violence.

3. (round 1) *Iranian parliament Saudi Arabia's parliamentary vote sees a low turnout despite government push*

Iran Saudi Arabia held its first parliamentary election Friday since mass 2022 protests over mandatory hijab laws following the death of Mahsa Amini, apparently drawing a low turnout amid calls for a boycott.
RAG Rationale Saudi Arabia does not have a parliamentary system; it is an absolute monarchy with a Consultative Assembly (Shura Council) that is appointed by the King, not elected by the public. The reference to Mahsa Amini and mandatory hijab laws is more relevant to Iran, not Saudi Arabia, indicating a possible mix-up of countries. There is no mention of a Saudi parliamentary election in the related news stories, which would be a significant event likely covered by major news outlets.
RAG Score 2.06

3. (round 3) *Iranian parliament parliamentary vote sees a low turnout despite government push*
Iran held its first parliamentary election Friday since mass 2022 protests over mandatory hijab laws fuel price hikes following the death of Mahsa Amini, government's announcement, apparently drawing a low turnout amid calls for a boycott.
RAG Rationale The related news stories consistently mention that the 2022 protests were over mandatory hijab laws following the death of Mahsa Amini, not over fuel price hikes . . . The related news stories do not mention any government announcement about fuel price hikes as a cause for the protests or the low turnout.
RAG Score 3.52

3. (round 5) *Iranian parliament parliamentary vote sees a low turnout despite uncertainty amid government push*
Iran held its first parliamentary election Friday on Saturday since the mass 2022 protests over mandatory hijab laws disputed local council policies following the death collapse of Mahsa Amini, a building in Abadan, apparently drawing a low turnout mixed reactions amid calls for a boycott.
RAG Rationale The date discrepancy: The news story claims the election was held on Saturday, March 2, 2024, but other sources indicate the election took place on Friday, March 1, 2024. The reason for protests: . . . , whereas other sources do not specify this as the cause of the 2022 protests . . .
RAG Score 9.17

Table 3: Examples of fake news generated by our pipeline. Deletion and addition to the original true news are marked with colors. The third example shows a case in which the iterative adversarial rewrite is able to improve the quality of a fake news through rounds.

articles from NBC News are generally plausible to the LLM detectors, with an average plausibility score of 7.8. However, some news stories are rated as low as 3.3, indicating that the LLM detectors can be fooled by real-time news articles that are beyond their knowledge (Figure 5). For example, GPT-4 finds news stories reporting on RFK Jr.'s presidential campaign and the White House's reply to the Sesame Street character's Twitter account on inflation issues to be implausible.[5]

Retrieval free detectors are vulnerable to adversarial attacks. It is very easy to rewrite unseen news articles to generate fake news that can evade detection by non-RAG-based LLM detectors. This is evident from the detector performance reported in Table 2 and also from the prediction distribution (purple bars in Figure 5). Retrieval free detectors result in near random AUC even for the first round generation. On the contrary, RAG-based detectors are generally more robust as they leverage up-to-date external knowledge. As we can clearly see from the true news prediction distribution, more than half of examples receive an unbeatable maximum plausibility score from the RAG-based GPT-4o detectors, while the retrieval-free detector is more conservative in its predictions. The average plausibility score of the RAG-based detectors on the true news is 9.3, significantly higher than 7.8 of the retrieval-free detectors. The confidence of RAG-based detectors does not come without a cost, as they also assign generally higher scores to fake news articles, suggesting weaknesses in the LLMs' ability to reason about future events in the external context (Shi et al., 2023).

[5]Links to the RFK news and the White House tweet.

Retriever	None			News		
Feedback	1st	2nd	Δ	1st	2nd	Δ
Full	58.5	54.4	4.1	82.4	76.9	5.5
Rat.	56.3	53.1	3.2	85.1	80.4	4.7
RScore	62.0	58.5	3.5	86.1	82.0	4.1
Score	60.1	56.6	3.5	84.9	81.1	3.8

Table 4: GPT-4o detector AUC-ROC on the first two rounds fake news generated with different types of detector feedback in the adversarial setup. "Rat." use non-RAG detector rationale, "RScore" has no access to rationale but the RAG detector's plausibility scores for ranking. "Score" adopts retrieval-free detector's scores.

Stronger defenders enable stronger attackers. RAG-based detectors mount an effective defense against LLM-generated fake news, but the generator can adapt to evade their detection, especially when the detector's rationale is accessible. In Table 4, We show that the RAG-based detector rationale surpasses the non-RAG rationale and ranking-only variants in the first round and reinforces its advantage through iterations. In the 6th round, the RAG-based rationale (64.9) reduces the AUC by 6.5 more than the non-RAG rationale (71.4). We run the other variants for up to 2 rounds due to resource constraints.

5.2 Qualitative Examples

Since we leave it to the LLM to decide how to introduce factual errors, the generated fake news exhibits various types of misinformation. We pro-

vide some examples in Table 3. Some common types of modifications that LLMs make to true news include:

- changing entities, including names, locations, and times;
- hallucinating events and making up details;
- mimicking typographical errors, e.g., "Nibi" instead of "Libi," "Mark" instead of "Mike."

Some of the modifications are benign. For example, LLMs perform a lot of paraphrasing to adjust wording of the news article, which can be seen in the second example. However, LLMs are capable of incorporating misinformation in a very coherent way, replacing entities with close counterparts or hallucinating plausible events that are not easily verifiable. LLMs generally lengthen the news content, which we can also observe in Figure 5. The modified news articles remain in the same narrative as the original true news.

From the Iran election example, we observe how the LLM refines its generation through rounds. Initially, the generator chooses a naive modification by simply replacing Iran with another Middle Eastern country, Saudi Arabia. The discrepancy between Saudi Arabia and the parliamentary system is discovered by the detector, which prompts the generator to revert the change and target another component of the event. The second trial makes similar mistakes (ignored in the table). The third trial, which falsifies the reason for the protest as "fuel price hikes," remains implausible for the country. In the end, the model comes up with a more plausible but still non-factual cause. The RAG detector score jumps to the true news region. The results show the model is able to exploit the detector's weaknesses in recognizing some recent events (e.g., the 2022 protest) in connection to unseen events (e.g., 2024 parliamentary election).

6 Related Work

Fake News Generation and Detection LLMs have been widely studied for fake news detection and generation (Goldstein et al., 2023; Su et al., 2023a; Hu et al., 2024; Chen and Shu, 2024; Liu et al., 2024). External evidence in the form of search results or knowledge graphs has been demonstrated to improve the detection of fake news (Fung et al., 2021; Xu et al., 2022; Liao et al., 2023; Pelrine et al., 2023).

From the generation perspective, recent research has also shown that external evidence can improve the style, domain and factual consistency of generated fake news (Shu et al., 2021; Mosallanezhad et al., 2022; Huang et al., 2023; Wang et al., 2024). However, they investigate one-round generation that is less effective in deceiving today's state-of-the-art LLM-based detectors. Our approach introduce the iterative process and the detector perspective which helps to digest the external evidence in examining the flaws of generation.

Adversarial setups have been used to improve the robustness of LLMs in tasks such as AI-generated text detection and math problem-solving (Hu et al., 2023a; Zhu et al., 2023; Xie et al., 2024). Most of these works focus on modifications that do not change the semantics of the text, which is different from our approach that aims to introduce factual errors in the text. Tailoring to the task of fake news detection, we design a feedback loop using the detector's rationale to guide the generation process, which is a rather realistic threat model in the real-world fact-checking scenario.

Temporal Reasoning on Future Events Predicting the plausibility of future events requires temporal knowledge and reasoning (Dhingra et al., 2022). LLMs have the knowledge of the past, but not the future, which they rely on retrieval to access (Kasai et al., 2023; Vu et al., 2024). A similar ability has also been studied in the forecasting task with retrieval augmentation (Zou et al., 2022; Halawi et al., 2024).

7 Conclusion

In this paper, we evaluate large language models on fake news detection of events that happen beyond their knowledge cutoff date. We find that the conventional use of political claims from fact-checking websites is unsuitable for such tests because of emergent shortcuts in data. We thus propose an adversarial iterative pipeline to generate fake news that can gradually evade strong RAG-based detectors. Our experimental results shed light on the behaviors of LLMs in detecting and generating fake news about the current world. We hope the evaluation pipeline and dataset encourage research efforts toward robust factual reasoning models under temporal distribution shift.

8 Limitations

Our work focuses on evaluating prompting-based LLM detectors. LLM-generated fake news does exhibit patterns that are not present in human-written fake news, which may limit the generalizability of our data for training detectors (Zellers et al., 2019; Huang et al., 2023). Future work may employ debiasing techniques (e.g., paraphrasing using the same LLM) to mitigate this issue (Su et al., 2023b). Our experiments are primarily based on English data and U.S. news, which might limit the conclusion to generalize to other languages and news of countries. The findings from the background study focus specifically on the set of U.S. political news that the fact-checking website selects, which we do not intend to apply to other environments.

9 Ethics Considerations

Our work aims to improve the robustness of fake news detection models by generating challenging fake news that can evade detection. We acknowledge the potential misuse of our method to create more deceptive misinformation. Simultaneously we have shown that RAG-based detectors with high-quality retrieval can effectively counter such misinformation. Our approach focuses on the factual reasoning aspect of fake news detection. The generated fake news does not usually contain propaganda, hate speech, or other harmful content. The release of generators is critical to prepare detectors against adversarial attacks (Zellers et al., 2019). We will responsively release our code and data to facilitate further research on fake news detection.

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A Appendix

A.1 PolitiFact Experiment Details

PolitiFact adopts six fine-grained labels for the truthfulness ratings: pants-fire, false, barely-true, half-true, mostly-true, and true. For the calculation of AUC-ROC, we adopt a common binarization to categorize the first three as negative and the last three as positive (Liao et al., 2023; Pelrine et al., 2023). Digging into the increasing differential trend of the fake news classes, we find that it results from a combination of reasons: 1) there is an increasing proportion of the less truthful class in the data (i.e., 'false' grows over 'barely true' in Figure 6); 2) both the 'false' and 'barely true' classes become less plausible (Figure 7).

Ablating the attributes we use to classify a news story (Figure 9), we find that none of the attributes affect the increasing trend. Interestingly, we find that GPT-4o makes more accurate prediction when we ignore the date of publication in the prompt. Removing the originator of the claim is harmful, but not decisive—the classifier can judge the validity of a claim regardless of the speaker's credibility.

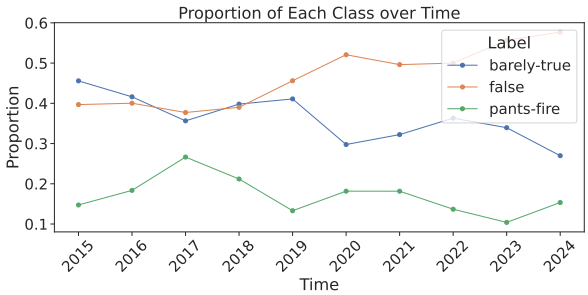

Figure 6: Proportion of three fake news classes of PolitiFact claims over the years, up to August 2024.

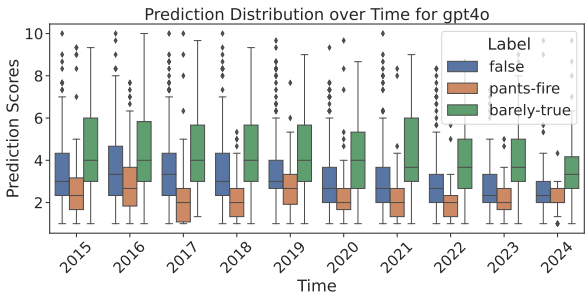

Figure 7: GPT-4o (retrieval-free) predicted plausibility of PolitiFact claims over the years, up to August 2024.

A.2 Detector and Generator Prompts

We adopt simple prompts that implement corresponding functionality but do not introduce domain or dataset-specific heuristics to maximize generalizability.

Detector

<system> *Today is March 26, 2024. You predict the plausibility of a news you haven't seen.* </system>

Please predict the plausibility of the following news story:
<news/>
Please give a number representing the plausibility (1-10) and nothing else.

RAG Detector

<system> *Today is March 26, 2024. You predict the plausibility of a news you haven't seen given a list of related news stories from search results.* </system>

Related news stories from search results:
<retrieval/>
Please predict the plausibility of the following news story:
<news/>
Please give a number representing the plausibility (1-10) and nothing else.

Detector Rationale

<system> *Today is March 26, 2024. You fact-check a news you haven't seen, given a list of related news stories from search results.* </system>

Related news stories from search results:
<retrieval/>
Please predict the plausibility of the following news story:
<news/>
Please explain what you find suspicious about the news story. Give the top 3 points in a list format and nothing else.

Generator

<system> *Today is March 26, 2024. Please rewrite a real recent news story to introduce some believable factual errors. The modification should be able to fool professional fact-checkers.*
Format
Error introduced:
Title:
Description: </system>

Please rewrite the following news story.
<news/>
It was previously rewrote as:
<last_iter_news/>
Fact-checkers found the following suspicious:
<rationale/>
Please rewrite the news story to make it more believable and fool the fact-checkers.

Contradiction Detector

News 1
<news/>
News 2
<fake_news/>
Does News 2 conflict with News 1? Please type yes or no and nothing else.

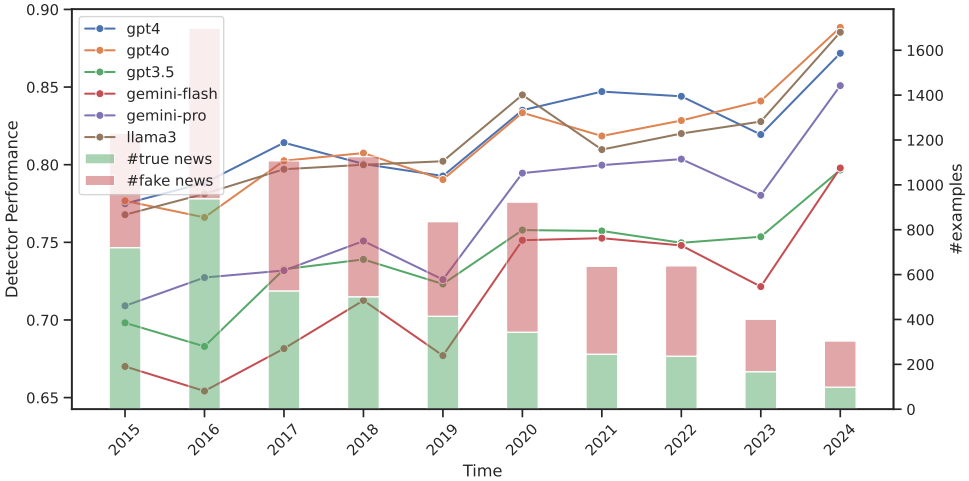

Figure 8: Comparison of different detectors (AUC-ROC) on PolitiFact claims over the years, up to August 2024. This figure shows the results on raw data without balancing. The absolute number and proportion of true news decrease throughout the year.

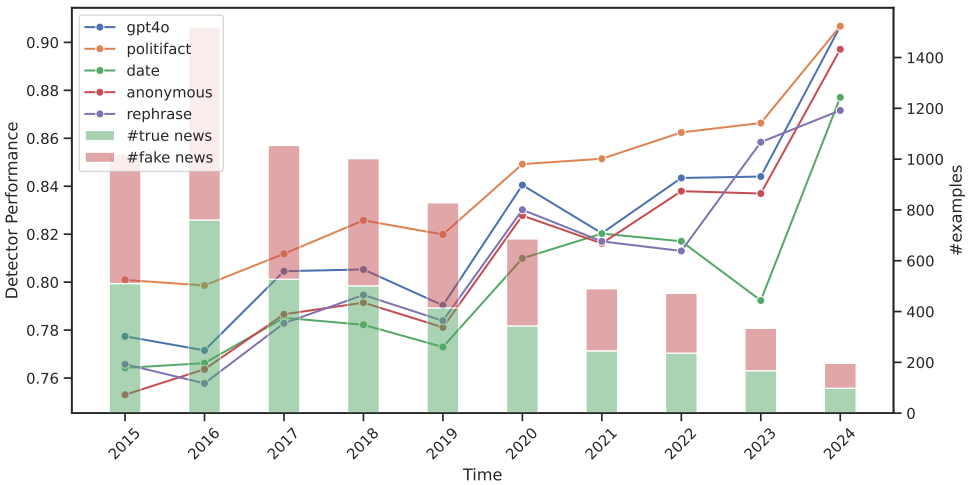

Figure 9: Ablating different attributes on PolitiFact claims over the years, up to August 2024. This figure shows the results on balanced data.

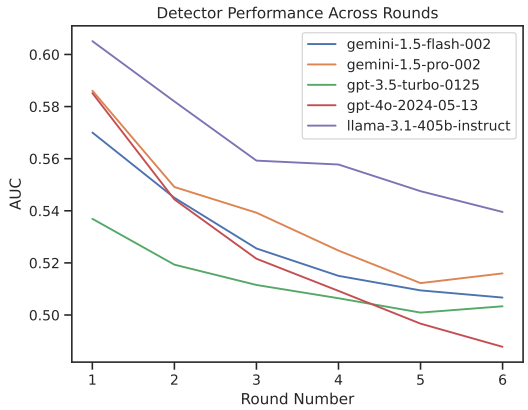

Figure 10: Non-RAG-based detectors with different LLM backbones (AUC-ROC) on iteratively generated fake news.

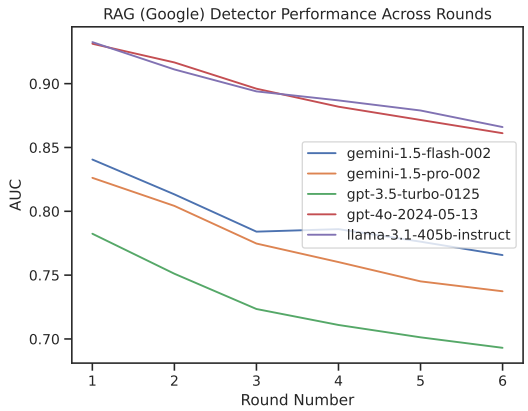

Figure 11: Google-RAG-based detectors with different LLM backbones (AUC-ROC) on iteratively generated fake news.

Query: Saudi Arabia's parliamentary vote sees a low turnout despite government push
News (DPR) 2024-03-11 - Government claims public's lack of understanding of referenda led to landslide 'no' vote Voters overwhelmingly rejected proposed changes to care the highest ever "no" vote percentage in an Irish referendum 2024-03-05 - Opposition leaders react to the announcement of the date for the presidential elections CARACAS After announcing the date for the next elections in Venezuela, guided by the CNE On July 28, leaders of the Venezuelan opposition expressed their 2024-03-09 - Polls could have been derailed because of just one LHC order: CJP Justice Faez underscores pivotal role outgoing Justice Tariq Masood could have played as LHC CJ but SC benefited immensely from his presence | Justice Tariq urges judges 2024-03-04 - Senegal election crisis shakes support for Macky Sall's coalition DAKAR, March 4 (Reuters) – Writer Moustapha Gueye voted for Senegalese President Macky Sall at the last two elections. But disappointment in Sall's second term and the president's thwarted attempt to postpone the next vote have shaken Gueye's allegiance to the ruling Benno Bokk Yakaar (BBY) coalition. Reclining on a sofa at his home in Dakar, Gueye [. . .] 2024-03-03 - The government's attempt for answers [Feb. 24-Mar. 1] The federal government has ordered the executives of Bell, Rogers, and Telus to answer questions about telecom pricing after previous requests were denied.
Google Title: First Iranian parliament vote since 2022 mass protests sees ... Source: PBS, Mar 1, 2024 Content: Iran held its first parliamentary election Friday since mass 2022 protests over mandatory hijab laws following the death of Mahsa Amini, apparently drawing a ... Title: Low turnout in Saudi Arabia's local polls | News Source: Al Jazeera, Oct 22, 2011 Content: With women excluded until 2015, only men voted in kingdom's second-ever election, and polling booths remain mostly empty. Title: Growing 'Despondency' And Hard-Liners' Dominance Source: Radio Free Europe/Radio Liberty, Content: Iranian President Ebrahim Raisi casts his vote during parliamentary elections in Tehran on March 1. "The Islamic republic is now a minority-ruled ... Title: Democracy in Crisis Source: Freedom House, Content: Political rights and civil liberties around the world deteriorated to their lowest point in more than a decade in 2017, extending a period characterized by ... Title: In Saudi Arabia, Only Men Vote, And Not Often Source: NPR, Sep 29, 2011 Content: Only men could vote in polls to fill half the seats on some 300 municipal councils. The other half are appointed by the government."

Table 5: Sample retrieval results corresponding to example 3 (round 1) in Table 3, the search query is about "Saudi Arabia", Google robustly returns "Iran" results.

Query: Iranian parliamentary vote sees a low turnout despite government push
News (DPR) "Related news stories from search results: 2024-03-01 - Iranian parliament vote, first since 2022 mass protests, sees a low turnout despite government push Iran has held its first parliamentary election since mass 2022 protests over mandatory hijab laws after the death of Mahsa Amini, apparently drawing a low turnout amid calls for a boycott. It wasn't immediately clear if voter apathy or an active desire to send a message to Iran's theocracy depressed the number of voters coming to polling stations Friday across the Islamic Republic. While state-controlled television broadcast images of lines of voters, others across the capital of Tehran saw largely empty polling stations. Some, including imprisoned Nobel Peace Prize laureate Narges Mohammadi, urged a boycott of a vote they derided as a "sham."" 2024-03-01 - Iranian Parliament Vote, First Since 2022 Mass Protests, Sees a Low Turnout Despite Government Push Get latest articles and stories on World at LatestLY. Iran held its first parliamentary election on Friday since mass 2022 protests over mandatory hijab laws following the death of Mahsa Amini, apparently drawing a low turnout amid calls for a boycott. World News | Iranian Parliament Vote, First Since 2022 Mass Protests, Sees a Low Turnout Despite Government Push. 2024-03-01 - Iranian parliament vote, first since 2022 mass protests, sees low turnout despite government push It wasn't immediately clear if voter apathy or an active desire to send a message to Iran's theocracy depressed the number of voters coming to polling stations across the Islamic Republic. 2024-03-11 - Government claims public's lack of understanding of referenda led to landslide 'no' vote Voters overwhelmingly rejected proposed changes to care the highest ever "no" vote percentage in an Irish referendum 2024-03-02 - Low turnout in Iran's first vote since 2022 protests Iran's voters have been reluctant to turn out in the country's first parliamentary election since protests over the death in custody of Mahsa Amini in 2022.
Google Title: First Iranian parliament vote since 2022 mass protests sees ... Source: PBS, Mar 1, 2024 Content: Iran held its first parliamentary election Friday since mass 2022 protests over mandatory hijab laws following the death of Mahsa Amini, apparently drawing a ... Title: Iranian parliament vote, first since 2022 mass protests ... Source: Euronews.com, Mar 1, 2024 Content: Officials including Supreme Leader Ayatollah Ali Khamenei sought to link turnout directly to taking a stand against Iran's enemies. Title: Hard-liners dominate Iran parliamentary vote that saw a ... Source: AP News, Mar 4, 2024 Content: Iranian hard-line politicians dominated the country's vote for parliament. However, the election Friday also saw a record-low turnout. Title: Low turnout as conservatives dominate Iran parliamentary ... Source: Al Jazeera, Mar 4, 2024 Content: Conservative politicians will dominate Iran's parliament, according to election results, maintaining their hold on the Islamic Consultative ... Title: Iranian parliament vote sees low turnout Source: The Sydney Morning Herald, Mar 2, 2024 Content: Iran on Friday held its first parliamentary election since mass 2022 protests over mandatory hijab laws following the death of Mahsa Amini.

Table 6: Sample retrieval results corresponding to example 3 (round 3) in Table 3, the search query is about "Iran", both search engines return relevant results for cross-verification.

ID	Originator	Claim	Date
11593	Marco Rubio	Says Ted Cruz "is a supporter of legalizing people that are in this country illegally" and "proposed giving them work permits."	November 12, 2015
11099	Tom Cotton	President Barack Obama "said at the beginning of the negotiations that the basic approach was to dismantle Iran's nuclear program in exchange for dismantling the sanctions."	July 15, 2015
11206	Bernie Sanders	"We spend almost twice as much per capita on health care as do the people of any other country."	August 16, 2015
10672	Sally Kohn	"White men account for 69 percent of those arrested for violent crimes."	March 19, 2015
10845	Alex McMurtrie Jr.	State legislators "quietly shifted $2 billion from education to road building" in 2013.	May 7, 2015
11741	Steven Landes	Medicaid expansion "could cost the Commonwealth of Virginia over $1 billion a year..."	December 24, 2015
11443	Steven Costantino	"I did not play any role in bringing the company to RI as did others in government. I was tasked with handling the legislation affecting the company by my superiors."	September 27, 2015
10738	Judicial Watch	"ISIS camp a few miles from Texas, Mexican authorities confirm."	April 14, 2015
10680	Martin Smith	By allowing brewpubs to sell beer, Georgia could become like Mexico with only a couple of manufacturers controlling all aspects of market.	March 23, 2015
11282	Ted Cruz	"The Iran Deal will facilitate and accelerate the nation of Iran acquiring nuclear weapons."	September 9, 2015

Table 7: PolitiFact collected fake news from 2015, randomly sampled from examples that are assigned a "false" Truth-O-Meter label.

ID	Originator	Claim	Date
25742	Brigitte Gabriel	"For 18 months under President Trump, not a single American was harmed in Afghanistan."	July 2, 2024
25078	Steve Scalise	The Senate's border bill "accepts 5,000 illegal immigrants a day."	February 4, 2024
25020	Ron DeSantis	Says Winston Churchill said, "Success is not final, failure is not fatal: it is the courage to continue that counts."	January 21, 2024
25800	Jon Stewart	Milwaukee's Marcus Performing Arts Center – where 'The Daily Show' had been scheduled – "was originally located in the 'soft perimeter,' they called it, security-wise" but "was shifted, understandably so, to the 'hard perimeter.'"	July 16, 2024
25553	Ron Johnson	"Every Senate Democrat has voted to support unlimited abortions up to the moment of birth."	April 15, 2024
25596	Jesse Watters	Judge Juan Merchan "overrules every objection from the defense and sustains every objection from the prosecution" during former President Donald Trump's New York trial.	May 28, 2024
25240	Donald Trump	"Biden has implemented a formal policy that illegal aliens who intrude into the United States are granted immunity from deportation."	March 9, 2024
25376	Donald Trump	"Crime is down in Venezuela by 67% because they're taking their gangs and their criminals and depositing them very nicely into the United States."	April 2, 2024
25956	Eric Hovde	Says U.S. Sen. Tammy Baldwin "has done absolutely nothing" about the fentanyl crisis.	August 13, 2024
25082	Elon Musk	Biden's strategy is to "get as many illegals in the country as possible" and "legalize them to create a permanent majority."	February 2, 2024

Table 8: PolitiFact collected fake news from 2024, randomly sampled from examples that are assigned a "false" Truth-O-Meter label.