Synthetic Disinformation Attacks on Automated Fact Verification Systems

Yibing Du†*, Antoine Bosselut‡*, Christopher D. Manning†

†Stanford University  ‡EPFL
antoine.bosselut@epfl.ch, {yibingdu, manning}@stanford.edu

Abstract

Automated fact-checking is a needed technology to curtail the spread of online misinformation. One current framework for such solutions proposes to verify claims by retrieving supporting or refuting evidence from related textual sources. However, the realistic use cases for fact-checkers will require verifying claims against evidence sources that could be affected by the same misinformation. Furthermore, the development of modern NLP tools that can produce coherent, fabricated content would allow malicious actors to systematically generate adversarial disinformation for fact-checkers.

In this work, we explore the sensitivity of automated fact-checkers to synthetic adversarial evidence in two simulated settings: ADVERSARIAL ADDITION, where we fabricate documents and add them to the evidence repository available to the fact-checking system, and ADVERSARIAL MODIFICATION, where existing evidence source documents in the repository are automatically altered. Our study across multiple models on three benchmarks demonstrates that these systems suffer significant performance drops against these attacks. Finally, we discuss the growing threat of modern NLG systems as generators of disinformation in the context of the challenges they pose to automated fact-checkers.

1 Introduction

From QAnon’s deep state to anti-vaccination campaigns (Germani and Biller-Andorno 2021), misinformation and disinformation have flourished in online ecosystems. As misinformation continues to induce harmful societal effects, fact-checking online content has become critical to ensure trust in the information found online. However, manual efforts to filter misinformation cannot keep pace with the scale of online information that must be reliably verified to avoid false claims spreading and affecting public opinion. Consequently, new research in automated fact-checking explores designing systems that can rapidly validate political, medical, and other domain-specific claims made and shared online (Thorne and Vlachos 2018; Guo, Zhang, and Lu 2019).

Figure 1: Outline of our two settings for adversarial injection of poisoned content into fact-checker evidence repositories.

A popular emergent paradigm in automated fact-checking, Fact Extraction and Verification (FEVER; Thorne et al. 2018), frames the problem as claim verification against a large repository of evidence documents. As one of the first large-scale datasets designed in this framework, FEVER was released with 185k annotated claims that could be verified against Wikipedia articles. When checking a claim, systems designed in this framework search for related documents in the database, and retrieve relevant supporting or refuting evidence from these sources. Then, these systems evaluate whether the retrieved evidence sentences validate or contradict the claim, or whether there is not enough information to make a judgment. More recently, the SciFACT (Wadden et al. 2020) and COVIDFACT (Saakyan, Chakrabarty, and Muresan 2021) benchmarks re-purposed this framework for the sci-
entific domain by releasing datasets of medical claims to be verified against scientific content (Wang et al. 2020). While this framework has led to impressive advances in fact verification performance (Ye et al. 2020; Pradeep et al. 2021), current benchmarks assume that the available evidence database contains only valid, factual information.

However, check-worthy claims are often made about new events that may not be verifiable against extensive catalogues, and that must be checked rapidly to avoid strategic disinformation spread (Vosoughi, Roy, and Aral 2018). Consequently, deployed fact-checkers will need to operate in settings where their available evidence is collected from contemporaneous reporting, which may be inadvertently sharing the same misinformation, or which may be intentionally influenced by systematic disinformation campaigns. Currently, malicious actors remain limited by the cost of running disinformation campaigns (DiResta et al. 2018) and the risks of operational discovery, impeding the scale at which they can deploy these campaigns, and thus the balance of real and false content that fact-checkers must distinguish. However, the development of NLP tools capable of generating coherent disinformation (Zellers et al. 2019; Buchanan et al. 2021) would allow malicious actors to overload contemporaneous content with adversarial information (Brundage et al. 2018) and bias the evidence used by automated fact-checkers.

Furthermore, even in settings where claims may be verified against established and trusted knowledge, misinformation can still find its way into repositories of documents used by fact-checking systems (Kumar, West, and Leskovec 2016). Wikipedia, for example, which underlies FEVER and other benchmarks (Petroni et al. 2021), acknowledges that much of the content on the platform may be incorrect, and remain so for long periods of time. For example, the Croatian Wikipedia was contaminated by pro-nationalist bias over a period of at least 10 years. Moreover, studies have uncovered articles on Wikipedia that were edited to provide favorable accounts on specific topics (e.g., workers at a medical device company edited articles to present an optimistic view toward treatments that used their product). Modern NLP tools would allow malicious users to scale up production of disinformation on these platforms, and increase the perception of false consensus or debate on these topics.

In this paper, we evaluate whether automated disinformation generators can effectively contaminate the evidence sets of fact verification systems, and demonstrate that synthetic disinformation drastically lowers the performance of these systems. We define adversarial attacks in two settings: Adversarial Addition (ADVADD; §4), where synthetically-generated documents are added to the document base, and Adversarial Modification (ADVMOD; §4), where additional automatically-generated information is inserted into existing documents. In both settings, we curate a large collection of adversarial disinformation documents that we inject into the pipelines of existing fact-checking systems developed for the FEVER, SciFact, and COVIDFACT shared tasks.

Our results demonstrate that these systems are significantly affected by the injection of poisoned content in their evidence bases, with large absolute performance drops on all models in both settings. Furthermore, our analysis demonstrates that these systems are sensitive to even small amounts of evidence contamination, and that synthetic disinformation is more influential at deceiving fact verification systems compared to human-produced false content. Finally, we provide a discussion of our most important findings, and their importance in the context of continued advances in NLP systems.

2 Background

In this section, we review the formulation of automated fact checking as fact extraction and verification, and recent advances in automated generation of textual disinformation.

Automated Fact-checking: Task

Current systems research in automated fact-checking often follows the fact verification and extraction procedure of receiving a natural language claim (e.g., “Hypertension is a common morbidity seen in COVID-19 patients”), collecting supporting evidence from a repository of available documents (e.g., scientific manuscripts), and making a prediction about the claim’s veracity based on the collected supporting evidence. Below, we define the two stages of this pipeline: evidence retrieval and claim verification.

Evidence retrieval The evidence retrieval stage of fact verification systems is typically decomposed into two steps: document retrieval and sentence retrieval. During document retrieval, documents in the evidence repository that are relevant to the claim are selected. Existing methods typically use information retrieval methods to rank documents based on relevance (Thorne et al. 2018; Wadden et al. 2020) or use public APIs of commercial document indices (Hanselowski et al. 2019; Saakyan, Chakrabarty, and Muresan 2021) to crawl related documents. In the sentence retrieval stage, individual sentences from these retrieved documents are selected with respect to their relevance to the claim, often using textual entailment (Hanselowski et al. 2019), or sentence similarity (Thorne et al. 2018) methods. Typically, the number of retrieved sentences is capped for computational efficiency.

Claim verification The claim verification stage of the pipeline evaluates the veracity of the claim with respect to the evidence sentences retrieved in the previous stage. Depending on the content found in the supporting sentences, each claim can typically be classified as supported (SUP), refuted (REF), or not enough information (NEI, though some benchmarks omit this label). Systems must aggregate and weigh the evidence sentences to predict the most likely label.

1https://www.lawfareblog.com/outsource-disinformation
2https://en.wikipedia.org/wiki/Wikipedia:Wikipedia_is_not_a_reliable_source
3https://meta.wikimedia.org/wiki/Croatian_Wikipedia_Disinformation_Assessment-2021
4https://www.theatlantic.com/business/archive/2015/08/wikipedia-editors-for-pay/393926/

We will release these documents under a Terms of Use to promote research in fact-checking systems in adversarial settings.

8Our code can be found at: https://github.com/Yibing-Du/adversarial-factcheck
We briefly describe the provenance and structure of our study. Would struggle to detect (Clark et al. 2021). With these claims when they were posted on the subreddit. The evidence is composed of documents provided /r/COVID19 contains 1,296 crowd-sourced claims. Refuted claims were automatically-generated by Goldberg’s perfect 173-0 streak ended at Starrcade 1998 after Kevin Nash scored the fateful pinfall with the help of Scott Hall and his taser gun. Specific studies have focused on whether neural language models could be used to generate disinformation that influences human readers (Kreps, McCain, and Brundage 2020, Buchanan et al. 2021). One such study directly explored this possibility by training GROVER, a large-scale, billion-parameter language model on a large dataset of newswire text with the goal of generating text that resembles news (Zellers et al. 2019). In human evaluations of the model’s generated text, the study found that human readers considered the synthetically-generated news to be as trustworthy as human-generated content. While the authors found that neural language models could identify fake, generated content when finetuned to detect distributional patterns in the generated text, they hypothesized that future detection methods would need to rely on external knowledge (e.g., FEVER).

### Automated Fact-checking: Datasets

Our method, ADVERSARIAL ADDITION (ADVADD), uses GROVER to produce synthetic documents for a proposed claim, and makes these fake documents available to the fact verification system when retrieving evidence. As GROVER requires a proposed article title and publication venue (i.e., website link) as input to generate a fake article, we use each claim as a title and set the article venue to wikipedia.com. We generate 10 articles for each claim and split them into paragraphs (n.b., FEVER DB contains first paragraphs of Wikipedia articles and SciFact contains abstracts of scientific articles). Statistics for the number of documents generated for each benchmark are reported in Table 3. Additional implementation details for the experimental setting of each benchmark can be found in the Appendix.

### Synthetic Disinformation Generation

Recent years have brought considerable improvements in the language generation capabilities of neural language models (Lewis et al. 2020, Ji et al. 2020, Brown et al. 2020, Holtzman et al. 2020), allowing users of these systems to pass off their generations as human-produced (Ippolito et al. 2020). These advances have raised dual-use concerns as to whether these tools could be used to generate text for malicious purposes (Radford et al. 2019, Bommasani et al. 2021), which humans would struggle to detect (Clark et al. 2021).

#### Table 1: Sample ADVADD document excerpts generated by GROVER for the FEVER and SciFact datasets.

| FEVER Claim | Starrcade was an annual professional wrestling event that began in 1988. |
|-------------|-------------------------------------------------------------------------|
| Original    | Starrcade (1988) was the sixth annual Starrcade professional wrestling pay-per-view (PPV) event produced under the National Wrestling Alliance (NWA) banner. |
| GROVER      | Starrcade was a monthly professional wrestling event for the decades between 1988 and 2003 that ran for the entirety of a weekend in Boston, Mass. |
| Media Cloud | Goldberg’s perfect 173-0 streak ended at Starrcade 1998 after Kevin Nash scored the fateful pinfall with the help of Scott Hall and his taser gun. |

| SciFact Claim | Taxation of sugar-sweetened beverages had no effect on the incidence rate of type II diabetes in India. |
|--------------|----------------------------------------------------------------------------------------------|
| Original     | The 20% SSB tax was anticipated to reduce overweight and obesity prevalence by 3.0% and type 2 diabetes incidence by 1.6% among various Indian subpopulations over the period 2014-2023. |
| GROVER       | ... analysis of a “cone-by-one” kind of survey question in India reached out to -9 145 trillion, including 2,557 separate instances of type II diabetes (which is comparable to the prevalence rate in Pakistan) ... |

- **FEVER**: The FEVER testbed (Thorne et al. 2018) is a dataset of 185,445 claims (145,449 train, 19,998 dev, 19,998 test) with corresponding evidence to validate them drawn from articles in Wikipedia. Because of its scale and originality, the FEVER dataset is one of the most popular benchmarks for evaluating fact verification systems (Yoneda et al. 2018, Nie, Chen, and Bansal 2019, Zhou et al. 2019, Zhong et al. 2020, Subramanian and Lee 2020).

- **SciFact**: The SciFact dataset (Wadden et al. 2020) contains 1,409 expert-annotated scientific claims and associated paper abstracts. SciFact presents the challenge of understanding scientific writing as systems must retrieve relevant sentences from paper abstracts and identify if the sentences support or refute a presented scientific claim. It has emerged as a popular benchmark for evaluating scientific fact verification systems (Pradeep et al. 2021).

- **COVID**: The COVID dataset (Saakyan, Chakrabarty, and Muresan 2021) contains 1,296 crowd-sourced claims crawled (and filtered) from the /r/COVID19 subreddit. The evidence is composed of documents provided with these claims when they were posted on the subreddit along with resources from Google Search queries for the claims. Refuted claims were automatically-generated by altering key words in the original claims.

### 3 ADVERSARIAL ADDITION: Evidence Repository Poisoning

In this section, we simulate the potential vulnerability of fact-checking models to database pollution with misinformation documents by injecting synthetically-generated false documents into the evidence sets of fact verification models, and assess the impact on the performance of these systems.

#### Approach

Our method, ADVERSARIAL ADDITION (ADVADD), uses GROVER to produce synthetic documents for a proposed claim, and makes these fake documents available to the fact verification system when retrieving evidence. As GROVER requires a proposed article title and publication venue (i.e., website link) as input to generate a fake article, we use each claim as a title and set the article venue to wikipedia.com. We generate 10 articles for each claim and split them into paragraphs (n.b., FEVER DB contains first paragraphs of Wikipedia articles and SciFact contains abstracts of scientific articles). Statistics for the number of documents generated for each benchmark are reported in Table 3. Additional implementation details for the experimental setting of each benchmark can be found in the Appendix.
Evidence CorefBERT Acc. KGAT Acc. MLA Acc. (Ye et al. 2020) (Liu et al. 2020b) (Kruengkrai et al. 2021)

| Evidence        | CorefBERT | KGAT | MLA |
|-----------------|-----------|------|-----|
| Total REF NEI   | 73.05 74.03 72.07 | 70.76 72.50 69.01 | 75.92 78.71 73.13 |
| Original        |           |      |     |
| ADVADD-min      | 34.80 24.72 22.38 | 34.08 48.63 19.52 | 50.93 73.04 48.81 |
| ADVADD-full     | 28.59 39.63 17.54 | 29.02 42.45 15.59 | 51.86 71.84 31.87 |
| ADVADD-oracle   | 21.18 27.09 15.26 | 23.43 31.47 15.38 | 29.05 29.76 28.33 |

Table 2: Effect of ADVADD on FEVER claim verification. We **bold** the largest performance drop relative to the original evidence.

**FEVER Study**

**Setup** For the FEVER benchmark, we select three high-ranking models from the leaderboard with open-source implementations: KGAT (Liu et al. 2020b), CorefBERT (Ye et al. 2020), and MLA (Kruengkrai, Yamagishi, and Wang 2021). For document retrieval, all models use the rule-based method developed by Hanselowski et al. (2019), which uses the MediaWiki API to retrieve relevant articles based on named entity mentions in the claim. For each claim and poisoned document, we extract all keywords and retrieve associated Wikipedia pages. If we find overlaps between the associated Wikipedia pages of a claim and a poisoned document, then the poisoned document is matched with the claim for document retrieval. Once the retrieved documents are available, the KGAT and CorefBERT models use a BERT-based (Devlin et al. 2019) sentence retriever to rank evidence sentences based on relevance to the claim (trained using pairwise loss). The MLA sentence retriever expands on this approach with hard negative sampling from the same retrieved documents to more effectively discriminate context-relevant information that is irrelevant to the claim. Claim verifiers vary between models, but are generally based off pretrained language models (e.g., CorefBERT, MLA) or graph neural networks (e.g., KGAT). We use the REF and NEI claims from the FEVER development set to study how the preceding systems are affected by the introduction of poisoned evidence.11

**Impact of ADVADD** We report the overall (and claim-stratified) performance change of the tested models in Table 2. For all models, we see a significant performance drop when GROVER-generated paragraphs are introduced into the available evidence set (ADVADD-full), indicating that fact verification models are sensitive to synthetically-generated information. This drop approaches the performance of an oracle (ADVADD-oracle), where only GROVER-generated documents are made available as evidence.

As confirmation that these attacks work as expected, we depict in Figure 2 how model predictions change once the synthetic disinformation is added to the evidence set. A significant number of claims that were originally predicted as REF or NEI are now predicted as SUP with the injected poisoned evidence. Consequently, we conclude that the poisoned evidence affects the model’s predictions in the intended way, and that cross-label changes for different pairings are rare. Furthermore, we also find that replacing the retrieved poisoned evidence with random retrieved evidence from FEVERDB does not cause the same performance drop (∼7% vs. ∼30%), indicating that these effects are caused by the injection of poisoned evidence, and not merely the replacement of potentially relevant evidence (see Appendix A for further details).

**Effect of disinformation scale** We also evaluate a setting where the attack is limited to retrieving only a single contaminated evidence sentence (ADVADD-min). The performance drops in the min setting are still considerable, suggesting that even limited amounts of injected disinformation can significantly affect downstream claim verification performance.

Moreover, Figure 3 shows a histogram of the number of poisoned evidence sentences retrieved per claim and a strat-
We note that claims labeled NEI are far more sensitive to the (48.6% precision). While well-trained workers will improve (a,c) and NEI (b,d) claim verification accuracy for A
the potential for such an attack to remain undetected.
readers, pointing to the quality of the synthetic content, and
challenge of distinguishing these evidence sources for lay
at recognizing synthetic content, our results demonstrate the
do not distinguish machine- from human-generated evidence
mate the number of poisoned sentences (23.6% recall), and
humans underesti-
machine-generated. Our results show that humans underesti-
evidence examples (which could be from A
cal Turk where we presented three workers with five retrieved
quality to bypass potential human detectors. For 500 REF
poisoned evidence produced by A
Quality of poisoned evidence We also evaluate whether
poisoned evidence produced by ADVADD is of sufficient
quality to bypass potential human detectors. For 500 REF
and 500 NEI claims from FEVER, we ran a study on Mechani-
cal Turk where we presented three workers with five retrieved
examples (which could be from ADVADD or from FEVERDB) and asked them to identify which examples were

Figure 3: Degree of evidence poisoning and resulting REF
(a,c) and NEI (b,d) claim verification accuracy for ADVADD-
GROVER (a,b) ADVADD-MediaCloud (c,d)

Table 4: Statistics and performance relative to the source of
poisoned evidence: GROVER or MediaCloud

| Source         | Evidence Retrieval | Sentence |
|----------------|--------------------|----------|
| GROVER         | 87%                | 65%      |
| MediaCloud     | 99%                | 17%      |

Comparison with human-compiled online evidence
While we have shown that synthetic disinformation affects
the performance of downstream claim verifiers when present
in their evidence sets, the threat should be evaluated in com-
parison to the threat of already existing online misinformation
on the same topic. Consequently, we use the MediaCloud[12] content analysis tool to crawl web content related to FEVER
claims. We crawl English-language news since January 2018
that contains the keywords of a claim anywhere in their text
and extract articles with a title that contains at least one key-
word from the claim. Finally, we process these articles to have
the same format as the original Wikipedia database, yielding
74M total available documents for retrieval (Table 3).

In Table 4, we report the performance of an ADVADD
setting where only MediaCloud-crawled documents are avail-
able to the retriever compared to our original setting where
GROVER-generated documents were available. We observe
that evidence crawled from online content has less of an in-
fluence on downstream fact verification performance (∼3% vs.
∼40% performance drop). While we are able to retrieve
far more documents from MediaCloud due to the size of the
database (99% of claims retrieve a document from Media-
Cloud), the sentences from ADVADD-GROVER documents are selected more frequently in the sentence retrieval step.
While this gap would likely be less pronounced with more
contentious claims that yield competing viewpoints (Bush
and Zaheer 2019), these results demonstrate that synthetic dis-
information can be much more targeted to a particular claim
of interest. Figure 3 supports this conclusion, where we ob-
serve smaller performance drops for ADVADD-MediaCloud
(c,d) compared to ADVADD-GROVER (a,b) even when all
retrieved sentences are sourced from the poisoned evidence.

SCIFACT Study
Setup For SCIFACT, we chose three systems for testing
our attack: VeriSci (Wadden et al. 2020), ParagraphJoint (Li,
Burns, and Peng 2021), and SciKGAT (Liu et al. 2020a). The
VeriSci model was released by the creators of the SCIFACT
benchmark and retrieves relevant abstracts to a claim using
TF-IDF. The ParagraphJoint model, one of the top systems
We generate a RoBERTa-based model that predicts a veracity label. We generalize the information can still find its way into repositories of documents. Motivated by the possibility that merely introduces irrelevant content to the evidence document. We modify the original claims in two ways. For example, we alter a claim by applying heuristics such as number alteration, antonym substitution, and entity replacement with close neighbors according to embedding similarity. These modifications should not confuse humans, but would affect sensitive fact verification systems, providing a competitive method to retrieve abstracts. Both use a RoBERTa-based module for rationale selection and label prediction. The SciKGAT model uses the same evidence retrieval as VeriSci, but the KGAT model to verify claims. We use the 300 claims from the development set to evaluate our method. We generate GroVER articles as with FEVER, but we set the venue URL to medicalnewstoday.com, which produces articles more likely to reflect scientific and medical content.

**Results** In Table 5, we observe large performance drops across all metrics for all models. Furthermore, we note that our disinformation generator, GroVER, is not trained on large quantities of scientific documents of the same format as the original evidence. Despite producing documents that are stylistically different, the disinformation is still retrieved as evidence, and affects the performance of the verifier.

**COVIDFACT Study**

**Setup** We run our analysis on the baseline system from Saakyan, Chakrabarty, and Muresan (2021). This model retrieves evidence documents for claims using Google Search and then selects evidence sentences based on high cosine similarity between sentence embeddings of the claims and individual evidence sentences (Reimers and Gurevych 2019). A RoBERTa-based model predicts a veracity label. We generate ADVADD articles in the same manner as for SciFACT, and run our analysis on the 271 REF claims from the test set.

**Results** In both the Top-1 and Top-5 settings from Saakyan, Chakrabarty, and Muresan (2021), we observe a ¬14.4% performance drop on REF claims (83.8% → 69.4%). We note that COVIDFACT random and majority accuracy is only 67.6% due to a label imbalance.

### Table 5: Effect of ADVADD evidence on the SciFACT benchmark. We **bold** performance drops relative to the original evidence.

| Model                     | Evidence Set | Sentence selection | Sentence label | Abstract label | Abstract rationalized |
|---------------------------|--------------|--------------------|----------------|----------------|----------------------|
| VeriSci                   | Original     | 47.69              | 42.62          | 51.03          | 48.45                |
| (Wadden et al. 2020)      | ADVADD       | **27.05**          | **23.50**      | **25.57**      | **24.33**            |
| SciKGAT                   | Original     | 55.61              | 51.69          | 58.04          | 57.41                |
| (Liu et al. 2020a)        | ADVADD       | **39.44**          | **36.97**      | **37.46**      | **36.98**            |
| ParagraphJoint            | Original     | 53.63              | 43.59          | 55.52          | 49.55                |
| (Li, Burns, and Peng 2021)| ADVADD       | **37.68**          | **32.60**      | **41.31**      | **37.12**            |

4 **ADVERSARIAL MODIFICATION: Evidence Document Poisoning**

In Section 3, we investigated the effect of adding disinformation documents to the evidence repositories of fact verification systems, simulating the setting where the dynamic pace of news might lead to fake information being used to verify real-time claims. However, even in settings where information has more time to settle and facts to crystallize, misinformation can still find its way into repositories of documents used by fact-checking systems. Motivated by the possibility of malicious edits being made to crowdsourced information resources, we explore how NLP methods could be used to automatically edit existing articles with fake content at scale.

**Approach**

Our method, **ADVERSARIAL MODIFICATION (ADVMOD)**, simulates this setting in a two-stage process. First, we use off-the-shelf NLP tools to generate modified versions of the claim presented to the fact verifier. Then, we append our modified claims to articles in the evidence base that are relevant to the original claim. We modify the original claims in two ways.

In the **paraphrase** approach, we use a state-of-the-art paraphrasing model, PEGASUS (Zhang et al. 2019), to generate paraphrased versions of the original claim (see Table 4 for examples). These paraphrases generally retain the meaning of the claim, but often remove contextualizing information that would be found in the context of the article in which the new sentence is inserted. Because the paraphrase method attempts to produce synthetically different evidence that is semantically equivalent to the original claim, we test its efficacy relative to a method that merely introduces irrelevant content to the evidence document. Motivated by Jia and Liang (2017), we alter a claim by applying heuristics such as number alteration, antonym substitution, and entity replacement with close neighbors according to embedding similarity. These modifications should not confuse humans, but would affect sensitive fact verification systems, providing a competitive method to retrieve abstracts. Finally, our oracle reports the performance when the claim itself is appended to an evidence document.

**Results**

Our results in Table 5 demonstrate that injecting poisoned evidence sentences into existing documents is an effective method for fooling fact verification systems. Our ADVMOD-paraphrase method causes a significant drop on all tested models for both REF and NEI labeled claims. Furthermore, we also note that ADVMOD-paraphrase achieves larger performance drops than the baseline method, ADVMOD-KeyReplace, for most claim types (the KGAT model is slightly more sensitive to the baseline ADVMOD-KeyReplace for the NEI claims), indicating that injections of disinformation content are more effective than non-targeted perturbances to the evidence (e.g., ADVMOD-KeyReplace).
were more robust against claims that should be refuted.

Adding synthetic content to the evidence bases of fact verification will also be a liability when previously learned text repositories will be natural defenses against textual misinformation, some settings (Lee et al. 2020, 2021). While this property can be an advantage in using standalone language models as fact-checkers (Lee et al. 2020), language models pretrained on reliable fact-checker evidence (and their source), may still potentially decrease claim verification accuracy. While these results are troubling, we are optimistic that improvements in automated synthetic content detection, particularly by online platforms with considerable resources, combined with human audits of fact-checker evidence (and their source), may still potentially mitigate many attempted disinformation campaigns.

| Evidence | CorefBERT Acc. | KGAT Acc. | MLA Acc. |
|----------|----------------|-----------|----------|
|          | (Ye et al. 2020) | (Liu et al. 2020b) | (Kruengkrai et al. 2021) |
|          | Total | REF | NEI | Total | REF | NEI | Total | REF | NEI |
| Original | 73.05 | 74.03 | 72.07 | 70.76 | 72.50 | 69.01 | 75.92 | 78.71 | 73.13 |
| ADVMOD-KeyReplace | 53.83 | 66.50 | 41.15 | 42.82 | 68.90 | 16.74 | 60.93 | 81.83 | 40.02 |
| ADVMOD-paraphrase | 32.62 | 36.66 | 28.58 | 37.22 | 51.74 | 22.70 | 52.72 | 70.57 | 34.86 |
| ADVMOD-oracle (claim) | 4.78 | 7.94 | 1.61 | 11.90 | 23.78 | 0.02 | 25.17 | 45.96 | 4.37 |

Table 6: Effect of ADVMOD on FEVER claim verification. We **bold** the largest performance drop relative to the original evidence.

| Original | Damon Albarn’s debut album was released in 2011. |
| Paraphrase | Albarn’s first album was released in 2011. |
| KeyReplace | Stefan Blur’s debut album was released in 202. |
|          | Stefan Blur’s debut album was released in 1822. |

Table 7: Sample ADVMOD sentences

5 Discussion

Adding synthetic content to the evidence bases of fact verifiers significantly decreases their performance. Below, we discuss interesting findings and limitations of our study.

**Synthetic vs. human disinformation** As mentioned in Section 3, the performance of our test systems is more sensitive to poisoned evidence generated from GROVER than retrieved from MediaCloud, even if the number of documents retrieved from MediaCloud far exceeds the number generated from GROVER. While FEVER claims may not generally be worth opposing online (leading to less directly adversarial content being retrieved from MediaCloud), we note that language models have no such limitations, and can generate large quantities of disinformation about any topic. Consequently, while misinformation already makes its way into retrieval search results (Bush and Zaheer 2019), language models could cheaply skew the distribution of content more drastically (Bommasani et al. 2021), particularly on topics that receive less mainstream coverage, but may be of import to a malicious actor (Starbird et al. 2018).

**Language models as a defense** In the ADVADD and ADVMOD oracle settings, all tested systems performed better on claims labeled REF than for claims labeled NEI. This result implies that the GROVER-generated evidence was less adversarial for these claims, or that the pretrained models which these systems use to encode the claim and evidence sentences were more robust against claims that should be refuted. Consequently, we conclude that language models encode priors about the veracity of claims, likely from the knowledge they learn about entities during pretraining (Petroni et al. 2019), a conclusion also supported by contemporaneous work in using standalone language models as fact-checkers (Lee et al. 2020). While this property can be an advantage in some settings (i.e., language models pretrained on reliable text repositories will be natural defenses against textual misinformation), it will also be a liability when previously learned erroneous knowledge will counteract input evidence that contradicts it. Finally, we note that the presence of implicit knowledge in language models affecting the interpretation of input evidence implies that the training corpora of these LMs could be attacked to influence downstream fact verification. Prior work has explored poisoning task-specific training datasets (Wallace et al. 2021). As disinformation becomes more prevalent online, the pretrained corpora of LMs will require more careful curation to avoid learning adversarial content.

**Limitations** We identify three main limitations to our study. First, the FEVER document retrievers use the MediaWiki API to collect relevant Wikipedia articles based on entity mentions in the claim. We assume our synthetic content could be included in the retrieved documents if it were titled with a mention of the named entities in the claim. For SCI-FACT, this limitation is not present because synthetic abstracts are retrieved using statistical IR methods. Second, our method ADVADD uses the actual claim to generate the synthetic article. In the absence of explicit coordination, synthetic poisoned evidence would be generated without knowledge of the exact claim formulation, reducing the realistic correspondence between the claim and the synthetic disinformation. If the GROVER model directly copied the claim during generation, performance drops might be overestimated based on unrealistically aligned evidence. For the ADVADD-full setting, we measure that this issue arises in ~20% of claims, which are predicted incorrectly more often, but does not affect the conclusions of our study. Finally, our FEVER and COVIDFACT studies are run using only claims labeled as REF and NEI, which we discuss in more detail in the Appendix.

6 Conclusion

In this work, we evaluate the robustness of fact verification models when we poison the evidence documents they use to verify claims. We develop two poisoning strategies motivated by real world capabilities: ADVADD, where synthetic documents are added to the evidence set, and ADVMOD, where synthetic sentences are added to existing documents in the evidence set. Our results show that these strategies significantly decrease claim verification accuracy. While these results are troubling, we are optimistic that improvements in automated synthetic content detection, particularly by online platforms with considerable resources, combined with human audits of fact-checker evidence (and their source), may still potentially mitigate many attempted disinformation campaigns.
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A Additional ADVADD Results

Effect of increased evidence: When we increase the number of evidence sentences from 5 to 10 during the claim verification step, we see minimal difference in the performance drop. When only one adversarial sentence is inserted, the performance drop decreases from 23.87% for 5 sentences to 23.69% for 10 sentences for REF claims. For NEI claims, the performance drop actually increases from 49.49% (5 sentences) to 50.81% (10 sentences).

Effect of random evidence: The performance drops reported in Section 3 might be due to correct evidence being removed from the retrieved set, rather than poisoned evidence being introduced. To test this possibility, we ran an experiment where we replace the retrieved poisoned evidence sentences with randomly chosen sentences from FEVERDB. If poisoned evidence does not adversely affect the claim verifier beyond the replacement of potentially useful supporting sentences, we should expect minimal performance drop from this baseline. However, we find that when random sentences are inserted, the performance drop for the KGAT model shrinks from 30.05% to 6.63% for REF claims and from 53.42% to 7.73% for NEI claims. Similarly, in a proxy for the ADVADD-min setting, where only a single sentence is replaced, the shrink is from 28.87% to 1.86% for REF claims and from 49.49% to 7.01% for NEI claims. These results demonstrate that the performance drop comes from the addition of adversarial evidence instead of only the removal of possibly correct evidence, indicating that the claim verifier is directly sensitive to the content of poisoned evidence.

Effect of sentence retrieval performance: Our results in Table 2 show the MLA model (Kruengkrai, Yamagishi, and Wang 2021) is more robust to poisoned evidence. To explore the cause of this finding, we swap the sentence retrievers of the KGAT and MLA models to disentangle the contributions of their sentence retrievers and claim verifiers. In Table 8, we find that when the MLA sentence retriever is paired with the KGAT claim verifier, the performance of this joint system (highlighted in blue) increases relative to using the full KGAT model. Meanwhile, when paired with the KGAT sentence retriever, the MLA claim verifier achieves lower performance on REF claims (highlighted in red) than the full KGAT model, indicating that the strength of the MLA model may stem from a more powerful retriever. However, the MLA claim verifier is also more robust for NEI claims regardless of the retriever, implying that the claim verifiers of these models may suffer from exposure bias, whereby they overfit to their sentence retrievers during training. They learn to expect certain patterns from the evidence returned by these retrievers and when given evidence from another distribution (i.e., a different retriever) at test time, they perform worse on examples that require retrieval (i.e., REF claims).

B Additional ADVMOD Results

In Figure 4, we report additional ADVMOD results measuring the performance change as a function of the amount of documents we re-write in the document base. Our results show that editing multiple documents is more likely to cause the prediction to flip. However, even a single edit to an evidence document can often cause a large performance drop.
| **Original SUP Claim** | Ron Weasley is part of the Harry Potter series as the eponymous wizard’s best friend. |
|------------------------|---------------------------------------------------------------------------------|
| **Manual Counterclaim** | Ron Weasley is part of the Harry Potter series as the eponymous wizard’s worst enemy. According to the ‘Harry Potter: The Story of Ron Weasley’ campaign, the prince of Goblet of Fire and Hogwarts castle is part of the series as the eponymous wizard’s worst enemy. |
| **Automatic Counterclaim** | Ron Weasley is part of the Harry bee series as the eponymous wizard’s best friend. Unlike the remainder of Harry Potter, Ron Weasley is more than just a character on the Hogwarts kiddie roster. |
| **GROVER Output** | Bessie Smith was a singer. |
| **Manual Counterclaim** | Bessie Smith cannot sing. Bessie Smith, a kindergarten teacher in Chicago, Illinois, is scheduled to perform for the 2014 Eagles open game against the Giants on Monday Night Football (18:00 ET on ESPN). |
| **Automatic Counterclaim** | Bessie Smith was a vegetarian. So how did Bessie Smith become a vegetarian? The black American woman sat on the United States House Floor as a member of the Congressional Choir during the 70s, when she actually was a vegan. |
| **GROVER Output** | |

Table 9: Sample ADVADD document excerpts generated by GROVER for SUP claims in the FEVER dataset.

C Performance on Supports Labels

Our studies on the FEVER and COVIDFACT benchmarks focused on the claims labeled refutes (REF) and not enough information (NEI). Claims labeled as supports (SUP) were not included in the study due to the challenge of generating effective poisoned evidence for them. Generating poisoned evidence for FEVER NEI and REF claims is more straightforward because we can use variants of the claim (e.g., paraphrases) or the claim itself as input to GROVER to produce poisoned evidence. However, poisoned evidence can only be generated for SUP claims if suitable counterclaims can be formulated as an input to GROVER.

To test our method on SUP claims, counterclaims were generated in the following manner: we adapted the automatic counterclaim generation method from Saakyan, Chakrabarty, and Muresan (2021), which selects salient words in the original claim using an aggregate attention score for each token based on how much it is attended to by the other tokens in the sequence. Then, the most salient token is replaced by sampling from a masked language model. Once we generate a set of counterclaims using this method, we validate them using the decomposable attention NLI model of Parikh et al. (2016) by selecting the ones with the highest contradiction score with respect to the original claim. Then, we provided these counterclaims as inputs to GROVER to generate poisoned evidence. However, we found this method was not effective for generating poisoned evidence. When we ran our ADVADD setting using the KGAT model, we observed a surprising performance increase from 86.2% to 87.5% on label prediction accuracy, indicating that the generated poisoned evidence unexpectedly helps the model make correct predictions.

Examples in Table 9 depict the limitations of this approach. In the first example, the change made to generate the counterclaim does not change the semantics of the claim, merely changing the word “Potter” to “bee,” which is not a coherent counterclaim that would produce poisoned evidence from GROVER refuting the original claim. In the second example, the counterclaim is coherent, but does not semantically contradict from the original claim, making the poisoned evidence less likely to be retrieved when the original claim is provided to the fact verification model. Furthermore, we note the difficulty of generating counterclaims for many claims in FEVER. First, many of the original claims are not easily falsifiable (e.g., “Girl is an album”), making it challenging to formulate a suitable counterclaim. Other are statements that cannot be falsified without using explicit negation terms (e.g., “Stripes had a person appear in it”). As language models struggle to understand inferences of negated statements (Kassner and Schütze 2020; Jiang et al. 2021), GROVER may just as often generate content that ends up supporting the original claim, rather than contradicting it, when seeded with such explicitly negated counterclaims.

However, the focus of our study is whether synthetically-generated adversarial evidence could be generated at scale to mislead fact verification systems. While generating counterclaims automatically at scale is necessary to perform this study on FEVER SUP claims, an adversary would be more likely to generate synthetic content for a single claim (or related claims) of interest (rather than a large set). Consequently, they would be able to manually write the counterclaim that was needed to generate poisoned evidence, mitigating the need for automatic counterclaim generation methods. We evaluate this possibility by writing counterclaims for a sample of 100 FEVER SUP claims, allowing us to guarantee semantic contradiction of the original claim by the counterclaim (as seen in Table 9). However, we find that, once again, performance does not drop as the original performance on these claims was 92% and rose to 93% once the poisoned evidence from GROVER was available. Though manually writing contradicting statements guarantees coherence and quality of the counterclaim, GROVER may still fail to generate content as intended and may even affirm the original claim, possibly because the model has been trained on Wikipedia, indicating that GROVER may encode implicit knowledge about many
of the entities for which it must produce poisoned evidence, as discussed in Section 5. For example, we note that one of the counterclaims from Table 9 — “Bessie Smith was a vegetarian” — does not relate to singing at all. However, the GROVER model produces singing-related content anyway (Bessie Smith was a singer).

## D Reproducibility Details

This paper relies on the existing FEVER, SciFACT, and COVIDFACT datasets, which are publicly available. To test our method, we use the same evaluation metrics proposed by the dataset authors: label accuracy for FEVER [Thorne et al. 2018], the sentence selection, sentence label, abstract label, and abstract rationalized metrics for SciFACT [Wadden et al. 2020], and the Top-1 and Top-5 label accuracy for COVIDFACT [Saakyan, Chakrabarty, and Muresan 2021]. We also introduce our own datasets of adversarial evidence generated by GROVER and PEGASUS [Zhang et al. 2019]. They will be made publicly available with a license that allows for research use. For computational experiments in this paper, the main source code is available at:

https://github.com/Yibing-Du/adversarial-factcheck

These experiments were run on an NVIDIA Quadro RTX 8000 GPU. Because we do not train these models from scratch, but instead use existing released models, we only run each evaluation once since the result is deterministic. Consequently, there are no hyperparameters to tune. We use the default hyperparameters provided with the codebases of the models evaluated.