NSF-SciFy: Mining the NSF Awards Database for Scientific Claims

Anonymous ACL submission

Abstract

We introduce NSF-SciFy, a comprehensive dataset of scientific claims and investigation proposals extracted from National Science Foundation award abstracts. While previous scientific claim verification datasets have been limited in size and scope, NSF-SciFy represents a significant advance with 2.8 million claims from 400,000 abstracts spanning all science and mathematics disciplines. We present two focused subsets: NSF-SciFy-MatSci with 114,000 claims from materials science awards, and NSF-SciFy-20K with 135,000 claims across five NSF directorates. Using zero-shot prompting, we develop a scalable approach for joint extraction of scientific claims and investigation proposals. We demonstrate the dataset's utility through three downstream tasks: non-technical abstract generation, claim extraction, and investigation proposal extraction. Fine-tuning language models on our dataset yields substantial improvements, with relative gains often exceeding 100%, particularly for claim and proposal extraction tasks. Our error analysis reveals that extracted claims exhibit high precision but lower recall, suggesting opportunities for further methodological refinement. NSF-SciFy enables new research directions in large-scale claim verification, scientific discovery tracking, and meta-scientific analysis.

1 Introduction

The overall growth rate of scientific publications is estimated to be 4% annually, with a doubling time of 17 years (Bornmann et al., 2021). Within this deluge, researchers, reviewers, and the general public struggle to separate substantiated claims from spurious ones—whether it is the "quantum supremacy" assertions in computing, the short-lived excitement over LK-99 superconductors[3], or the misunderstanding surrounding microplastic leaches from black plastic spatulas[4]. Manual verification of ever growing body of scientific claims has become intractable, yet the economic and societal consequences of unverified claims are increasingly severe.


```
{
  "award_id": 2321365,
  "title": "Electrically Conductive 2D Metal-Organic Frameworks and Cova
  "technical_abstract": "Owing to their diverse potentials to serve as a
  "non_technical_abstract": "Sustaining the rapid advances of modern ele
  "verifiable_claims": [
    "MOFs and COFs have synthetic accessibility, structural modularity,
    "Electrical conductivity remains one of the most elusive traits of M
    "In 2D MOFs, electronic conduction can occur within the planes throu
    "In 2D COFs, pi-stacked layers represent the primary transport pathw
     ...
  ],
  "investigation_proposals": [
    "Develop and implement a new design strategy to promote long-range c
    "Incorporate built-in alternating pi-donor\/acceptor stacks inside 2
    "Investigate how pi-donor\/acceptor stacks consisting of different c
    "Create a new design strategy for next-generation electrically condu
    "Produce novel electrically conductive 2D MOFs and COFs with unique
     ...
  ],
  "publications": [
    {
      "doi": "10.1021\/acs.inorgchem.3c02647",
      "status": "resolved",
      "title": "From a Collapse-Prone, Insulating Ni-MOF-74 Analogue to
      "abstract": "Electrically conductive porous metal-organic framewor
    }
     ...
  ]
}
```


Figure 1: A sample record from our dataset. Each record contains 1) Award ID and title, 2) NSF Directorate, 3) Technical and non-technical abstracts, 4) Scientific Claims, 5) Investigation Proposals, and 6) Associated publications, when present.

Wadden et al. (2020) introduced the task of scientific claim verification with the SciFACT dataset, focusing primarily on automatic verification of scientific claims. Follow up works (see Section 2 for a detailed account) have mostly focused on the healthcare, building datasets from scientific publications, and modest-sized dataset creation. In this work, we relax all of these aspects and look at building at least an order of magnitude large-scale

[3] for an entertaining digression c.f., https://en.wikipedia.org/wiki/LK-99

[4] c.f., https://nationalpost.com/news/canada/black-plastic

Dataset	# claims	# docs	Evidence Source	Domain
SciFACT (Wadden et al., 2020)	1.4K	5K	Research papers	Biomedical
PubHEALTH (Kotonya and Toni, 2020)	11.8K	11.8K	Fact-checking sites	Public health
CLIMATE-FEVER (Diggelmann et al., 2020)	1.5K	7.5K	Wikipedia articles	Climate change
HealthVer (Sarrouti et al., 2021)	1.8K	738	Research papers	Healthcare
COVID-Fact (Saakyan et al., 2021)	4K	4K	Research, news	COVID
CoVERT (Mohr et al., 2022)	300	300	Research, news	Biomedical
SciFACT-Open (Wadden et al., 2022)	279	500K	Research papers	Biomedical
NSF-SciFy-MatSci (ours)	**114K**	**16K**	**NSF award abstracts**	**Material Science**
NSF-SciFy-20K (ours)	**135K**	**20K**	**NSF award abstracts**	**All Science & Math**
NSF-SciFy (ours)	**2.8M**	**400K**	**NSF award abstracts**	**All Science & Math**

Table 1: This table comparison clearly illustrates the scale advantage of NSF-SciFy over existing scientific claim verification datasets. While previous datasets like SciFACT and PubHEALTH contain at most thousands of claims from published research papers or fact-checking sources, our NSF-SciFy-MatSci and NSF-SciFy-20K datasets individually contribute more than 100K claims. The full NSF-SciFy dataset represents an order-of-magnitude increase with 2.8M claims across 400K abstracts spanning all science & math disciplines. This work introduces grant abstracts as a novel, untapped source for scientific claim extraction, complementing existing approaches that focus on published literature, news articles, or social media content.

scientific claim dataset covering all of basic science. We envision building of such large-scale, scientific claim datasets to help future work on robust scientific claim verification systems.

We introduce NSF-SciFy[1], a comprehensive dataset of claims and investigation proposals extracted from National Science Foundation (NSF) award abstracts. We choose NSF abstracts as our source material for several reasons:

1. NSF is a primary driver of U.S. scientific innovation, funding approximately 25% of all federally supported basic research, spanning the entirety of science and math areas, with an annual budget of $9.9 billion (FY 2023). Any claim dataset derived from the NSF awards database should faithfully represent the scientific Zeitgeist.
2. NSF's rigorous subject matter expert-review process provides an high-quality filter for the claims made in funded proposals.
3. The public availability and permissive usage terms of the NSF awards database makes it an excellent resource for open science research.
4. Previous datasets on scientific claims have been derived from scientific papers, but claims in scientific grants, and particularly investigation proposals, remain unstudied.

While not this focus of this paper, grant award abstracts, additionally, provide a unique opportunity to study the relationship between what researchers claim and what they propose to investigate. This could offer valuable insights into scientific practice and the evolution of research questions.

In this paper, we make the following contributions: (1) We introduce NSF-SciFy, the largest scientific claim dataset to date with 2.8M claims extracted from 400K NSF award abstracts, establishing grant proposals as a novel source for scientific claim extraction; (2) We create NSF-SciFy-MatSci focusing exclusively on materials science with 114K extracted claims from 16K abstracts. This is the first materials science claim dataset and, in number of extracted claims, this alone is an order of magnitude bigger than the largest publicly available claim dataset; In addition, we also create NSF-SciFy-20K with 135K claims spanning five NSF directorates. (3) We develop a zero-shot prompting approach for joint extraction of scientific claims and investigation proposals as a scalable way to bootstrap high-precision, large-scale scientific claim datasets; (4) We present novel evaluation metrics for claim/proposal extraction based on LLM judgments, showing that fine-tuned models significantly outperform base models; and (5) Finally, we release all datasets and trained models from our work for unfettered research and commercial use. Our dataset and methods enable new opportunities for large-scale claim verification, scientific discovery tracking, and meta-scientific research.

2 Related Work

Scientific claim extraction and verification has emerged as an important research area as the volume of scientific literature continues to grow expo-

[1]Short for "NSF SCIentific FeasibilitY".

nentially. Previous work has primarily focused on claims from published papers, fact-checking sites, and news articles.

Scientific Claim Datasets Several datasets have been developed for scientific claim verification, but all have focused on claims from published literature, while we undertake the study of grant award abstracts. SciFACT (Wadden et al., 2020) contains 1,400 scientific claims derived from research papers in the biomedical domain. PubHEALTH (Kotonya and Toni, 2020) includes 11,800 claims from journalists and fact-checkers in public health. CLIMATE-FEVER (Diggelmann et al., 2020) compiled 1,500 claims from news articles about climate change. HealthVer (Sarrouti et al., 2021) extracted 1,800 claims from search queries related to health topics. COVID-Fact (Saakyan et al., 2021) and CoVERT (Mohr et al., 2022) focused on COVID-19 related claims from social media. SciFact-Open (Wadden et al., 2022) expanded the original SciFact dataset using information retrieval pooling, yet it still remains health-care focused and a few orders of magnitude smaller than our largest dataset.

Table 1 situates existing scientific claim datasets with our NSF-SciFy datasets, highlighting the significantly larger scale of our contribution (2.8 million claims in NSF-SciFy, 135,000 claims inNSF-SciFy-20K and 114,000 claims in NSF-SciFy-MatSci), broad topic coverage (all of science and math), and novelty of data source (grant abstracts). See Figure 2.

Meta Science and Social Science Previous works have examined grants data in social science and meta-science contexts. For example, Park et al. (2024) examine the relationship between interdisciplinary grants and the impact of papers they support and Xu et al. (2022) study the influence of research funding on team structure using grant data. While these are tenuously connected to our work, we list them for the sake of completeness.

3 Building NSF-SciFy

3.1 Data Collection

We downloaded the entire NSF Awards database[2] in XML format, containing more than 0.5 million awards from 1970 through September 2024. After parsing, we obtained 412,155 parseable awards, which we call NSF-SciFy.

[2] https://www.nsf.gov/awardsearch/advancedSearch.jsp

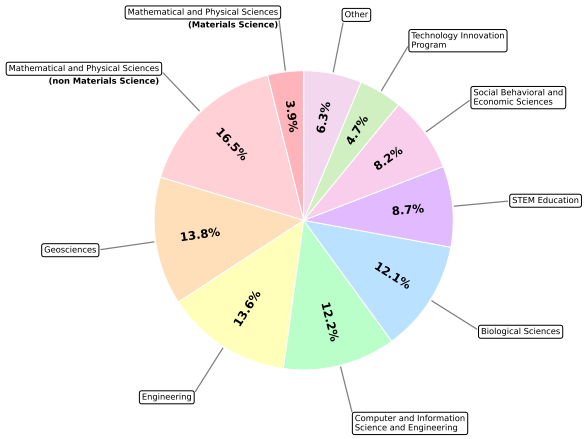

Figure 2: Distribution of awards areas as represented by the National Science Foundation directorates in NSF-SciFy, illustrating the breadth and comprehensiveness of scientific claims in our dataset. The NSF-SciFy-MatSci subset spanning all of materials science awards represents 3.9% of the entire dataset.

In this paper, we focus on all awards from the Division of Materials Research (DMR), which is responsible for most materials science awards at the NSF. This subset, called NSF-SciFy-MatSci, contains 16,031 awards, representing approximately 3.2% of the entire NSF awards database. We chose materials science as our focus due to its interdisciplinary nature and technological importance. In addition, we build NSF-SciFy-20K, a different subset of 20K awards spanning 5 NSF directorates — Mathematical and Physical Sciences (MPS), Geological Sciences (GEO), Engineering (ENG), Computer and Information Science and Engineering (CSE), and Biological Sciences (BIO).

3.2 Data Processing

As Figure 1 illustrates, each record in NSF-SciFy-MatSci typically contains:

1. Award ID, title, and year.
2. Directorate and division information
3. Technical abstract
4. Non-technical abstract (present in ∼81% of awards)
5. Scientific claims made in the abstracts
6. Investigation proposals in the abstracts
7. Publications resulting from the grant (when available)

The practice of updating awards with resulting publications is relatively recent, primarily occurring from 2014 onwards. For awards where publications are present, we extracted the DOIs and

resolved them to obtain titles, abstracts, and publication URLs.

3.3 Claim and Investigation Proposal Extraction

To extract scientific claims and investigation proposals from the award abstracts, we developed a zero-shot prompting approach using Anthropic's Claude-3.5[3] model. Our prompt instructed the model to identify two types of statements:

1. **Verifiable claims**: Statements that the abstract claims to be true or states as assumptions, either explicitly or implicitly.
2. **Investigation proposals**: Forward-looking statements that propose specific research activities as part of the award.

We structured the prompt to return a JSON object containing the award ID, technical abstract, non-technical abstract, a list of verifiable claims, and a list of investigation proposals. To maintain consistency and quality, we set temperature to zero for all extractions. See Appendix A for the exact prompt and Appendix G for sample claims and investigation proposals.

We performed qualitative experiments with several prompt variants and our analysis showed that jointly extracting claims and investigation proposals helped maintain the relevance of extracted claims. When claims were extracted without also extracting investigation proposals, the model often confused forward-looking statements about proposed investigations as factual claims.

4 Dataset Analysis

NSF-SciFy The full dataset contains 412,155 award abstracts spanning from 1970 to 2024, with 2.8 million scientific claims and corresponding investigation proposals.

NSF-SciFy-MatSci This materials science subset, which is the focus of this preprint, contains:

- 16,042 awards with each with a technical and non-technical abstract
- 114K extracted scientific claims (average of 7 ± 2 claims per abstract-pair)
- 145K extracted investigation proposals (average of 9 ± 3 proposals per abstract-pair)
- 2,953 awards with linked publications (18.4% of the dataset). Such awards had anywhere between 1 – 4 publications.

[3] `Claude-3.5-Sonnet-20240620` accessed between Sep-Oct. 2024, to be specific

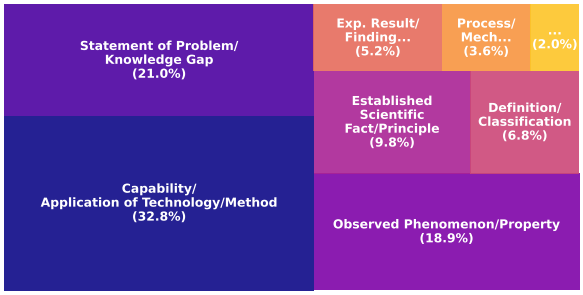

Figure 3: A treemap of the scientific claim categories in NSF awards. See Section 4.2 for descriptions of these categories.

NSF-SciFy-20K For building models across all NSF directorates, we take 20,000 sample subset of NSF-SciFy, by stratifying across 5 directorates.

- 20,001 awards with each with a technical and non-technical abstract
- 135K extracted scientific claims (average of 7 ± 2 claims per abstract-pair)
- 139K extracted investigation proposals (average of 7 ± 2 proposals per abstract-pair)

4.1 Technical vs. Non-Technical Abstracts

We investigated the differences between technical and non-technical abstracts in our dataset. Using a symmetric BLEU score to measure textual similarity between paired abstracts, we found that only 202 (1.5%) out of 13,025 technical/non-technical abstract pairs had a similarity score greater than 0.6, suggesting that the non-technical abstracts are not simply copied from the technical abstracts.

Since grant abstracts are previously unexamined in literature, we further investigated the stylistic differences between technical and non-technical abstracts using pre-trained document embedding models. Figure 5 compares content embeddings from SPECTER (Cohan et al., 2020) and style embeddings from STEL (Patel et al., 2025). Using these embeddings with a linear SVM classifier, we achieved F1 scores of 90.99 (SPECTER), 88.42 (STEL), and 89.99 (concatenated), demonstrating that the abstracts are distinguishable both in content and style.

4.2 A Taxonomy of Scientific Claims in NSF Award Abstracts

To understand the nature of assertions made in NSF award abstracts, we analyzed and grouped 810 extracted claims over a stratified sample of 120 awards spanning 5 NSF directorates – MPS, GEO, ENG, CSE, and BIO – resulting in the identifica-

tion of eight distinct categories. These categories encompass a range of scientific statements: **Established Scientific Fact/Principle** refers to claims that state well-accepted scientific laws or widely known facts. **Observed Phenomenon/Property** includes claims describing natural phenomena or material properties that have been observed. Claims detailing the function, potential, or application of a specific technology, method, or material fall under **Capability/Application of Technology/Method**. **Hypothesis/Theoretical Prediction** categorizes claims that propose theoretical explanations, predictions, or hypotheses requiring further verification. Specific results, findings, or statements about measurability are grouped under **Experimental Result/Finding/Measurability**. **Statement of Problem/Knowledge Gap** highlights existing problems, limitations, or gaps in current knowledge or technology. Claims that define terms or classify entities are categorized as **Definition/Classification**. Finally, **Process/Mechanism Description** includes claims that describe physical or chemical processes or mechanisms. Figure 3 shows the distribution of these claim types, and Table 10 lists examples for each of these types. As one might expect in grant applications, the most common claim type is "Capability/Application of Technology/Method" (32.8%), followed by "Statement of Problem/Knowledge Gap" (21.0%) and "Observed Phenomenon/Property" (18.9%).

4.3 Evaluating the Extracted Verifiable Claims

To evaluate how good the claim extraction from Section 3.3 is, we annotated the abstracts in the 120 sampled awards (see Section 4.2) with claims and computed precision and recall. Figure 4 summarizes the precision, recall, and F1-scores of the extracted claims for all 6 areas of interest. The areas of interest include, Materials Science (DMR) Mathematical and Physical Sciences except Materials Science (MPS-DMR), Geological Sciences (GEO), Engineering (ENG), Computer and Information Science and Engineering (CSE), and Biological Sciences (BIO). We notice from Figure 4 a near perfect precision for the extracted claims in all areas. Although our LLM-derived dataset suffers from recall, we hope that training on a massive corpus of high quality claims will result in useful claim extraction systems. We consider our findings on claim extraction as directional and skip a similar evaluation for investigation proposals.

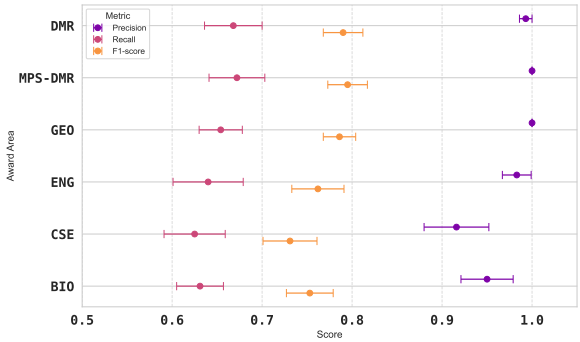

Figure 4: A Cleveland dot plot of precision, recall, and f1-score across different NSF Award Areas for claims extracted via Claude (See Section 3.3). Error bars denote standard deviation (bootstrap N=1000). See Section 4.3 for analysis.

5 Tasks, Metrics, and Experiments

We designed three NLP tasks to evaluate the utility of our dataset:

1. The **Non-technical Abstract Generation** task translates dense, technical grant abstracts into accessible language for broader science communication. Motivated by capturing the core scientific essence while navigating stylistic and content differences between technical and lay summaries, this task uses the dataset's paired examples (common in NSF awards) to train models for this nuanced transformation.
2. The **Abstract to Scientific Claims Extraction** task automates identifying verifiable assertions—the core of scientific discourse—from grant abstracts, which capture these claims at an early, pre-publication stage. Significant performance gains post-fine-tuning highlight the dataset's effectiveness in teaching models to pinpoint these crucial statements.
3. The **Abstract to Investigation Proposals Extraction** task distinguishes aspirational research intentions from established claims, offering a novel analysis of scientific texts. This provides a clearer view of the planned research trajectory by identifying intended activities. It complements claim extraction by presenting a fuller picture of proposed work, from assertions to investigative pathways, again showing significant fine-tuning efficacy due to the dataset's focused nature.

To explore the three tasks, we finetuned two 7B parameter language models:

- `Mistral-7B-instruct-v0.3` (Jiang et al., 2023)

Metric	Mistral	Qwen
BERTScore-P	0.8563 (+0.38% ↑)	0.8459 (+0.98% ↑)
BERTScore-R	0.8555 (+0.30% ↑)	0.8597 (+1.61% ↑)
BERTScore-F1	**0.8561** (+0.36% ↑)	0.8437 (+0.75% ↑)
ROUGE1	0.2000 (+2.58% ↑)	0.1978 (+1.98% ↑)
ROUGE2	0.0198 (+4.76% ↑)	0.0210 (+3.89% ↑)
ROUGE-L	0.1273 (+2.96% ↑)	0.1466 (+0.65% ↑)
ROUGE-L-sum	0.2166 (+2.45% ↑)	0.2078 (+1.66% ↑)

Table 2: Finetuning performance for `Mistral-7B-instruct-v0.3` and `Qwen2.5-7B-Instruct` models for Technical abstract to Non-technical abstract translation (Task 1), with relative improvements over the corresponding unfinetuned model indicated in green. Error bars for all metrics at 95% confidence intervals range between 0.0000–0.0025. Mistral model outperforms Qwen on almost all metrics for this task regardless of finetuning. We note that the percent changes, while statistically significant, are modest for this task indicating an excellent out-of-the-box performance that's challenging to improve upon.

- `Qwen2.5-7B-Instruct` (Yang et al., 2024)

Details about the finetuning can be found in Appendix E.

5.1 Evaluation Metrics

For Task 1 – abstract generation – we employed a comprehensive evaluation framework using both BERTScore (Zhang et al., 2020) and ROUGE (Lin, 2004) metrics to assess the quality of generated non-technical abstracts. This combination enables us to capture both lexical overlap and structural similarity through the ROUGE variants, while BERTScore provides insights into semantic alignment between the generated texts and reference abstracts. Incorporating such multi-viewed metrics[4] ensures that the evaluation reflects not only the presence of key words and phrases but also the underlying meaning and narrative coherence of the abstracts.

For Task 2 – claim extraction – we developed a novel evaluation approach using LLM-based comparisons. Previous methods for claim evaluations focused on comparing a single claim against a single document. See Tang et al. (2024), for example. However, our setting required evaluating a set of extracted claims against a gold set of claims.

Towards that end, we defined a boolean function $\mathbf{\Phi}_{\text{claim}}$ using `GPT-4o-mini` with zero-shot prompting to determine whether a generated claim is supported by a gold standard claim. See Appendix B for prompt details[5]. Using this function, we calculated precision and recall as follows:

$$\text{Precision} = \frac{1}{|S|} \sum_{c \in S} \max_{g \in G} \mathbf{\Phi}_{\text{claim}}(c, g)$$

$$\text{Recall} = \frac{1}{|G|} \sum_{g \in G} \max_{c \in S} \mathbf{\Phi}_{\text{claim}}(g, c)$$

where S is the set of claims generated from the finetuned model, after removal of any repeats/near-repeats [6], and G is the gold standard set. We note that this is a variant of precision/recall metrics defined for image captioning in (Deitke et al., 2024), however unlike Deitke et al., we explicitly use $\mathbf{\Phi}_{\text{claim}}$ in computing both precision and recall. This is necessary as we need to accurately penalize any spurious claims generated by the finetuned model. Works by (Gu et al., 2025; Liu et al., 2023) are relevant here.

Analogously, for Task 3 – extraction of investigation proposals – we define precision and recall similarly but use a different pairwise boolean judge function $\mathbf{\Phi}_{\text{IP}}$ *mutatis mutandis*. See Appendix C for prompt details.

6 Results

6.1 Non-technical Abstract Generation

Table 2 shows the results for Task 1. Both Mistral and Qwen models demonstrated strong performance, with fine-tuning providing modest improvements. The Mistral model outperformed Qwen on almost all metrics, achieving a BERTScore-F1 of 0.8561 after fine-tuning (+0.36% relative improvement). ROUGE scores were generally low (0.01-0.22), reflecting the stylistic differences between technical and non-technical abstracts.

6.2 Scientific Claim Extraction

For Task 2 (claim extraction), fine-tuning yielded substantial improvements. As shown in Table 3, the fine-tuned Mistral model achieved a precision of 0.7450 (+116.7% relative improvement), recall of 0.7098 (+59.5%), and F1 of 0.7097 (+101.8%). The Mistral model consistently outperformed Qwen, though both showed significant benefits from fine-tuning.

[4] For BERTScore we report precision, recall and F1, and for ROUGE we report ROUGE-1, ROUGE-2, ROUGE-L, and ROUGE-L-sum.

[5] We tried several slight edits of the prompts and found them to be robust to such changes.

[6] We determine repeats and near-repeats in the generation by thresholding cosine similarity calculated over a TF-IDF representation of the generated claims.

Metric	Mistral	Qwen
Precision	0.7450 (+116.7% ↑)	0.6839 (+107.1% ↑)
Recall	0.7098 (+59.5% ↑)	0.6611 (+7.8% ↑)
F1	0.7097 (+101.8% ↑)	0.6541 (+63.3% ↑)

Table 3: Finetuning performance for `Mistral-7B-instruct-v0.3` and `Qwen2.5-7B-Instruct` models for Claim Extraction from abstracts (Task 2), with relative improvements over the corresponding unfinetuned model indicated in green. Error bars for all metrics at 95% confidence intervals range between 0.0038–0.0055. Mistral model outperforms Qwen on almost all metrics for this task regardless of finetuning. We note the large positive percent changes, sometimes improvements as large as 2x, indicate finetuning is indispensable for claim extraction. Mistral model outperforms Qwen on almost all metrics for this task.

6.3 Investigation Proposal Extraction

Similarly, Task 3 (proposal extraction) showed dramatic improvements with fine-tuning. As shown in Table 4, the Mistral model achieved a precision of 0.7351 (+18.24%), recall of 0.7539 (+127.24%), and F1 of 0.7261 (+90.97%) after fine-tuning. The relative improvements were even larger for the Qwen model, though Mistral still performed better overall.

Metric	Mistral	Qwen
Precision	0.7351 (+18.24% ↑)	0.7245 (+70.07% ↑)
Recall	0.7539 (+127.24% ↑)	0.6865 (+81.57% ↑)
F1	0.7261 (+90.97% ↑)	0.6827 (+112.60% ↑)

Table 4: Finetuning performance for `Mistral-7B-instruct-v0.3` and `Qwen2.5-7B-Instruct` models for extraction of Investigation Proposals from award abstracts (Task 3), with relative improvements over the corresponding unfinetuned model indicated in green. Error bars for all metrics at 95% confidence intervals range between 0.0036–0.0073. Mistral model outperforms Qwen on almost all metrics for this task regardless of finetuning. We note the large positive percent changes, sometimes improvements as large as 2x, indicate finetuning is indispensable for this task. Mistral model outperforms Qwen on almost all metrics for this task.

Since Mistral models seemed to have an edge over the Qwen2.5 models for these tasks, we also trained a Mistral only version of on the NSF-SciFy-20K subset which spans all NSF directorates. The results for that can be found in Appendix F.

7 Error Analysis

Of the three proposed tasks, we consider the claim extraction task as a canonical task for performing error analysis. To do so, we consider another 120 awards from the test portion of NSF-SciFy-MatSci and NSF-SciFy-20K. These were stratified sampled across the five areas of interest (similar to Section 4.3). We then generate the claims using a Mistral-7B model finetuned on NSF-SciFy-20K, resulting in 802 claims. A careful examination revealed around 2.6% of the generated claims were incorrect. To dive deeper, we categorized the erroneous claims into 5 categories. We list them here with examples:

1. Overconfidence: The claim can be overconfident about information that has qualifiers in the supporting document text (award abstract).

> **Award ID:** 9820570
>
> **Extracted Claim:** The research areas include knot theory, immiscible fluids and geodesic nets, ergodic theory, commutative algebra and vector-valued forms.
> **Analysis:** The abstract states 'probably in the areas of,' indicating potential areas, not certainty.

2. Mixing Information: The claim can mix information from two sentences together to form wrong information.

> **Award ID:** 1205671
>
> **Extracted Claim:** The SEAQUEST experiment at Fermilab has successfully measured the asymmetry of up and down anti-quarks in the nucleon.
> **Analysis:** The abstract mentions that SEAQUEST will follow the successful E866 measurement with more precise data, and thus it does not say SEAQUEST has already successfully measured that, but the success is describing the previous E866.

3. Overgeneralization: The claim can overgeneralize what the supporting document implies.

> **Award ID:** 0957482
>
> **Extracted Claim:** The methodology is potentially environmentally benign.
> **Analysis:** The abstract mentions non-dangerous chemicals but does not specifically state that the methodology is environmentally benign.

4. Information Omission: The claim might omit important information from the abstract and thus the meaning is changed.

Award ID: 9409461

Extracted Claim: Frequency-domain techniques can display trade-offs between output performance and sensitivity reduction.
Analysis: The claim frames output performance and sensitivity reduction as two separate quantities and leaves out bandwidth, so it does not accurately reflect the abstract.

5. Hallucinations about Administrative Metadata: The model can sometimes hallucinate claims regarding where the funding is from and which institutions are included. While hallucination is a serious issue, it is worth noting that for this dataset and model scientific claims seem to be rarely hallucinated. In our study, all hallucinations were connected with administrative metadata.

Award ID: 0542751

Claim: The award is funded under the American Recovery and Reinvestment Act of 2009 (Public Law 111-5).
Reasoning: This claim is not mentioned in the abstract.

To mitigate these errors, uncertainty calibration and prompting strategies can reduce overconfidence and overgeneralization, encouraging the model to reflect source qualifiers. Fine-tuning with more annotated data and enforcing stricter alignment between claims and source text can address mixing information and omission issues. Retrieval-augmented generation and chain-of-thought prompting may also promote better grounding. For hallucinations about administrative metadata, entity verification or output constraints based on structured data can help. Combining these approaches with human-in-the-loop evaluation might further improve claim extraction reliability.

We performed a similar error analysis on claims extracted from Claude (See section 3.3). Our findings revealed a smaller error-rate (2.1% as opposed to 2.6%), and of the only 10 erroneous claims, 5 were hallucinations of administrative data.

8 Discussion and Conclusion

We introduced NSF-SciFy, a large dataset of 2.8 million scientific claims and proposals from 400,000 NSF grant abstracts across all science and mathematics disciplines. Focused subsets include NSF-SciFy-MatSci (114,000 materials science claims) and NSF-SciFy-20K (135,000 claims from five directorates). Experiments demonstrate that fine-tuning language models on NSF-SciFysignificantly improves scientific claim and proposal extraction, with relative performance gains often exceeding 100%. Non-technical abstract generation saw modest improvements due to strong baselines. Stylistic differences between technical and non-technical abstracts offer potential for science communication. Our claim taxonomy identifies prevalent assertion types like capability/application and problem/knowledge gap statements. NSF-SciFy's unique advantages include its vast scale, high quality from NSF expert review, comprehensive coverage of scientific domains, a temporal span from 1970-2024 enabling longitudinal studies, and, for recent grants, links to resulting publications. Error analysis showed high precision but lower recall in claim extraction, with error categories guiding future improvements. NSF-SciFy opens new research avenues in large-scale claim verification, scientific discovery tracking, and meta-scientific analysis, a key resource for understanding scientific assertions at their origin.

9 Limitations

Source Material Scope. The dataset, derived from NSF award abstracts, offers insights into early-stage scientific claims from a rigorously reviewed, cross-disciplinary source. However, it currently excludes claims from unfunded proposals or international contexts. Future work may expand to other agencies and sources.

Extraction Methodology. Our approach utilizes zero-shot prompting with large language models, refined by prompt engineering and selective human validation. While manual evaluation shows high precision, some residual errors in recall and claim boundary identification may exist, especially for nuanced assertions. Fine-tuning on this dataset significantly improves extraction, indicating potential for further methodological refinement and broader annotation.

Evaluation Design. We introduced LLM-based metrics for evaluating claims and investigation proposals, offering a nuanced assessment beyond lexical overlap. These metrics correlate well with human judgment in samples, but broader validation across more scientific domains is needed to confirm their robustness. The public dataset and code aim to facilitate such community efforts.

Temporal and Linked Data Coverage. Spanning over five decades and including recent linked publication metadata, the dataset's systematic outcome tracking is limited for older awards. This restricts longitudinal analysis of claim evolution from proposal to publication. Broader, consistent outcome reporting could enrich NSF-SCIFY for deeper research trajectory studies.

Generalizability. While designed and validated for National Science Foundation abstracts, whose structure may differ from other scientific communications, the general framework is adaptable. It could be extended to related corpora like other funding agencies, patent abstracts, or scientific news, creating opportunities for future research.

10 Reproducibility Statement

To foster research on large-scale claim extraction, we are releasing our datasets, training code, and trained models:

- NSF-SCIFY-MATSCI: Materials Science subset with extracted claims, investigation proposals, and resolved publication information.
- NSF-SCIFY: Similar in content to NSF-SCIFY-MATSCI, but a larger superset spanning all of NSF awards database. The key difference is the claims and investigation proposals are extracted from our finetuned models instead of frontier LLMs.
- Our best finetuned model checkpoints for extraction of claims and investigation proposals at ___[7].

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Appendix

A Complete Prompt for Extracting Claims and Investigation Proposals

You are an expert materials science researcher. Given an input JSON description of an NSF material science award abstract, parse out the technical and nontechnical abstracts, and identify the verifiable claims and research/investigation proposals the abstract makes. Be thorough. Answer in the following JSON format:

```
{
  "award_id": "", // copied from input
  "technical_abstract": "" // technical
      abstract if present, otherwise
      contents of the abstract field in the
       input
  "non_technical_abstract": /non-technical
      abstract if present, otherwise empty
  "verifiable_claims": [ // list of strings
  ],
  "investigation_proposals": [ // list of
      strings
  ],
}
```

verifiable_claims are statements that the abstract claims to be true or states as an assumption explicitly or implicitly.
investigation_proposals are forward-looking statements that the abstract proposals to investigate as a part of this award.
Ensure that the output is in JSON format and that the JSON is valid.

We manually tested the prompt with a few award abstracts to make sure it was optimal for this task.

B Prompt for Task 2 evaluation function Φ_{claim}

Check two scientific claims c1 and c2, if c1

is supported by c2. If c2 includes all the evidences for c1, but also includes additional content, then it should still be supported (YES). If not all information of c1 is included in c2, or if c2 contains information that conflicts with information in c1, then it should be unsupported (NO). Answer only as a YES or NO.
c1: {c1}
c2: {c2}

C Prompt for Task 3 evaluation function Φ_{IP}

Check two investigation proposals c1 and c2, if c1 is supported by c2. If c2 includes all the investigations proposed by c1, but also includes additional proposals, then it should still be supported (YES). If not all proposed investigations by c1 is included in c2, or if c2 contains investigation actions that conflict with investigation actions in c1, then it should be unsupported (NO). Answer only as a YES or NO.
c1: {c1}
c2: {c2}

D Stylistic Differences between Technical and Nontechinal Abstracts

E Finetuning Details

E.1 Data Preparation

Starting with 16,042 processed entries in NSF-SciFy-MatSci, we removed near-duplicates in technical and non-technical abstracts using trigram Jaccard similarity (threshold > 0.9), resulting in 11,569 data points. We further filtered cases where character-level 10-gram similarity between an entry's technical and non-technical abstracts exceeded 0.6, yielding 11,141 final data points. We split this dataset into train/validation/test sets with 8,641/500/2,000 examples, respectively.

E.2 Finetuning Details

For fine-tuning, we used LoRA (Hu et al., 2021) with rank=128, lora_alpha=64 and a learning rate of 1e-5 scheduled linearly. We updated the query, key, value, and output projection layers, as well as MLP gate, up, and down projections. We ran the finetuning on an A100 GPU for 3 epochs, 100 warmup steps, and a batch size of 2 with 4 accumulated steps.

F Evaluation results for NSF-SciFy-20K

Tables 5, 6, and 7 summarize the results for the three generation tasks defined in Section 5 on NSF-SciFy-20K.

Model Metric	Base	Finetuned
BERTScore-F1	0.8514 ± 0.0003	0.8500 ± 0.0006
BERTScore-Precision	0.8515 ± 0.0003	0.8513 ± 0.0007
BERTScore-Recall	0.8516 ± 0.0003	0.8496 ± 0.0005
ROUGE-rouge1	0.3351 ± 0.0013	0.3141 ± 0.0023
ROUGE-rouge2	0.0705 ± 0.0008	0.0936 ± 0.0016
ROUGE-rougeL	0.1773 ± 0.0008	0.1967 ± 0.0016
ROUGE-rougeLsum	0.1982 ± 0.0010	0.1998 ± 0.0016

Table 5: Technical to Non-Technical Abstract Task: Mistral-7B

Model	Base	Finetuned
Precision	0.4146 ± 0.0025	0.7526 ± 0.0027
Recall	0.8141 ± 0.0026	0.7354 ± 0.0026
F-score	0.5247 ± 0.0025	0.7268 ± 0.0023

Table 6: Abstract to Claims Task: Mistral-7B

Model	Base	Finetuned
Precision	0.6222 ± 0.0038	0.7219 ± 0.0027
Recall	0.6364 ± 0.0034	0.7359 ± 0.0029
F1-score	0.5668 ± 0.0033	0.7039 ± 0.0026

Table 7: Abstract to Investigation Proposals Task: Mistral-7B

G Examples of Extracted Claims and Investigation Proposals

Tables 8 and 9 provide a sampling of the extracted claims and investigation proposals.

H Examples of Scientific Claim Categories

Please see Table 10 for the examples.

I AI Writing/Coding Assistance Disclosure

In accordance with the ACL Policy on AI Writing Assistance[8], the authors attest that we used generative AI tools for assistance purely with the language of the paper, including spell checking, grammar fixes, and proof reading. Additionally,

[8] https://www.aclweb.org/adminwiki/index.php/ACL_Policy_on_Publication_Ethics#Guidelines_for_Generative_Assistance_in_Authorship

we used GPT-4o to fix LaTeX issues, and to generate LaTeX tables from spreadsheets. In all such uses, the outputs were verified by the first author for correctness.

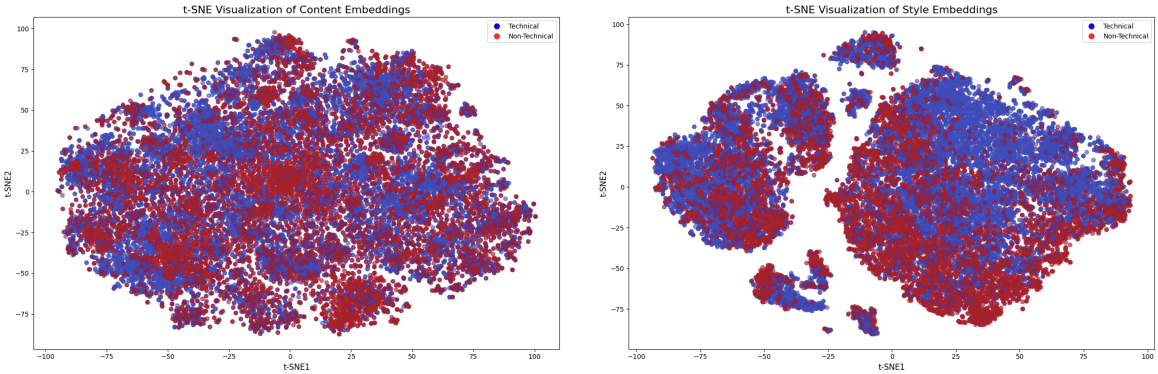

Figure 5: The t-SNE plot of comparing content embeddings from SPECTER (Cohan et al., 2020) and style embeddings from STEL (Patel et al., 2025) for technical and non-technical abstracts in NSF-SciFy-MatSci. The somewhat clear separation between technical and non-technical abstracts when using style embeddings indicate marked stylistic differences between the two kinds abstracts.

Award ID	Title	Extracted Claims
2324035	DMREF: Developing and Harnessing the Platform of Quasi-One-Dimensional Topological Materials for Novel Functionalities and Devices	["Topological insulators are electrically insulating in the bulk but host conductive surface states that are immune to impurities.", "Current TI materials face critical challenges that limit their potential.", "Quasi-1D structures promise to overcome challenges faced by current TI materials.", "Most identified topological insulators are either strongly bonded bulk materials or layered van der Waals materials.", ...]
9814055	Kinks and Surface Potentials	["Atomically flat terraced surfaces for thin TEM samples can be prepared under moderate (10-7 Torr) vacuum conditions by annealing in oxygen or vacuum for materials such as sapphire, SiC and MgO.", "\"Forbidden\" Bragg reflections arise from the stacking fault between partial dislocations.", "The surface potential is critical for chemical reactions at surfaces, adsorption, catalysis, epitaxy, diffusion bonding process, oxidation, and semiconductor crystal growth.", ...]
0821136	MRI: Acquisition of an Imaging Spherical Aberration Corrector and a Lorentz Lens for Magnetic Materials Characterization	["The attainable spatial resolution of uncorrected Lorentz instruments is in the range 10-15 nm.", "Delocalization effects cause significant image blurring in uncorrected Lorentz microscopes.", "Recent developments in aberration correction make it possible to correct the spherical aberration of a Lorentz lens.", "The size of written bits in state-of-the-art magnetic recording media is comparable to the magnetic resolution of uncorrected Lorentz microscopes.", "Transmission electron microscopes have suffered from lens aberration since their invention in the 1930s.", "The Hubble space telescope suffered from a similar aberration when first launched.", ...]

Table 8: A sample of extracted claims from the NSF-SciFy-MatSci dataset. Award IDs are hyperlinked to the NSF's Award database.

Award ID	Title	Extracted Investigation Proposals
2324035	DMREF: Developing and Harnessing the Platform of Quasi-One-Dimensional Topological Materials for Novel Functionalities and Devices	["Predict, design, synthesize, and control topological phases in quasi-1D topological materials.", "Design and demonstrate emergent materials, functionalities, and devices, including moir\'e quasi-1D TIs, stable and high temperature quantum spin Hall (QSH) insulators, and quantum intelligent sensors.", "Expand research to include other selected quasi-1D materials families through collaborations.", "Discover or realize novel topological materials and phases.", "Study topological phase transitions and control.", "Investigate room-temperature QSH effect.", ...]
9814055	Kinks and Surface Potentials	["Observe dislocation kinks by atomic resolution TEM in materials such as sapphire, SiC and MgO.", "Use \"forbidden\" Bragg reflections to form lattice images without surface noise.", "Determine which process (kink formation, kink migration or obstacles along the dislocation line) limits kink (and hence dislocation) velocity, for given conditions of temperature and stress.", "Extend quantitative convergent-beam TEM measurements of bonding in crystals to the RHEED geometry to refine the electrostatic potential extending into the vacuum from ceramic surfaces.", "Measure modifications to the surface potential resulting from the deposition of a monolayer or more of atoms.", ...]
0821136	MRI: Acquisition of an Imaging Spherical Aberration Corrector and a Lorentz Lens for Magnetic Materials Characterization	["Acquire an imaging spherical aberration corrector and a Lorentz lens for magnetic materials characterization.", "Add these components to an existing FEI Titan 80-300 TEM.", "Bring the spatial resolution in Lorentz mode down to less than 1 nm, with negligible delocalization effects.", "Enable direct quantitative study of magnetic features at a length scale of around 1 nm .", "Obtain new scientific results on material systems for which these observations were previously impossible.", "Impact a large number of research groups within CMU, as well as collaborations with local industry and several national laboratories.", ...]

Table 9: A sample of extracted investigation proposals from the NSF-SciFy-MatSci dataset. Award IDs are hyperlinked to the NSF's Award database.

Category: Capability/Application of Technology/Method
Memory-centric computing capitalizes on extensive parallelism in memory arrays.
The Illinois group has joined the fixed target COMPASS experiment at CERN.
An electronics company is involved in the project, making imaging products in this energy regime.
Category: Definition/Classification
The RV Weatherbird II is owned and operated by the Bermuda Biological Station for Research (BBSR), Inc.
The program will include topics such as dark matter, dark energy, inflation, and gravitational waves.
The shear zone in question is the Cuyamaca-Laguna Mountains shear zone.
Category: Statement of Problem/Knowledge Gap
Current efforts on analyzing tree-informed compositional data are primarily designed for individual applications.
CU began the Guerrero GPS project in 1997.
High pressure-low temperature metamorphism is often obscured by post-tectonic thermal equilibration or later deformation and mineral growth.
Category: Experimental Result/Finding/Measurability
Lattice QCD has made important progress.
RBP repression is absent when an oncoprotein is present.
Over 100 of 650 U.S. electronics fabricators have gone out of business in the past five years, according to a 1999 White Paper by the Interconnection Technology Research Institute.
Category: Established Scientific Fact/Principle
Dynamic programming includes well-known search algorithms like breadth-first search, Dijkstra's algorithm, A*, value iteration and policy iteration for Markov decision processes.
The electron carries a magnetic moment.
Stars in clusters evolve off the main sequence, become red giants, and ultimately horizontal branch stars.
Category: Observed Phenomenon/Property
The lake level of Laguna Paron was artificially lowered in 1985.
Laminated sediments are exposed in Laguna Paron, Peru.
The study sites exhibit extreme differences (1 to 2 orders of magnitude) in larval settlement.
Category: Process/Mechanism Description
Exciton-phonon and exciton-exciton interactions contribute to decoherence at finite temperatures.
The fidelity of translation is determined by the accuracy of aminoacyl-tRNA selection by ribosomes and synthesis of cognate amino acid/tRNA pairs by aminoacyl-tRNA synthetases.
The evaluation process includes both direct and indirect measures of student success and learning.
Category: Hypothesis/Theoretical Prediction
Assemblages that combine human-technology partnerships are stronger than individual humans or machines.
Mating advantage in guppies appears to result from female sexual responses to unusual males.
The long wavelength part of the CBR spectrum is important for constraining the evolution of the intergalactic medium.

Table 10: Scientific claim categories found in NSF-SciFy and 3 randomly selected examples for each category.