Structured Understanding of Social Media Discourse: An Automated Framework for Taxonomy Construction

Haiqi Zhang
University of Texas at Arlington
haiqi.zhang@mavs.uta.edu

Abstract

The rapid spread of misinformation on social media presents a significant challenge for public discourse and decision-making. Identifying and categorizing factual claims from social media platforms is essential to understand the online discourse and combat the influence of misleading information. This thesis proposal introduces a novel framework for the automated construction of taxonomy of factual claims on social media. The framework leverages large language models (LLMs) and human-in-the-loop annotations to accurately identify distinct factual claims and organize them into a multi-tiered taxonomy. It provides an organized way to manage and explore factual claims, making the analysis of online discourse more efficient and insightful.

1 Introduction

Misinformation, also known as false or misleading information (Wu et al., 2019), has the potential to sway public perception, propagate confusion, and influence decision-making processes (Del Vicario et al., 2016; Muhammed T and Mathew, 2022). The prevalence and velocity of misinformation dissemination have substantially increased in the digital era, particularly through social media platforms that facilitate the rapid spread of content, mixing truths with falsehoods (Allcott et al., 2019). Factual claims, which are assertions verifiable as true or false, are a common vehicle for misinformation (Ni et al., 2024). These factual claims, regardless of their accuracy, profoundly affect society as they are often accepted as true by the public (Ognyanova et al., 2020; Xiao et al., 2021; Moravec et al., 2018; Zhang et al., 2024).

The dynamic nature of social media can lead to the repetition or reformulation of these claims, which complicates the task of identifying and verifying factual content (Zhou et al., 2015). This presents significant challenges for stakeholders in various fields, including public health, political science, and social science, who need to analyze large volumes of social media data and understand the nuances of misinformation (Suarez-Lledo and Alvarez-Galvez, 2021; Hook and Verdeja, 2022; Muhammed T and Mathew, 2022). Traditional methods, such as manual coding and content analysis, are overwhelmed by the volume and complexity of unstructured social media language (Amundsen, 2022). Manual approaches can also be time-consuming, prone to human biases, and lack scalability (Toivonen et al., 2019; Canhoto and Padmanabhan, 2015; Amundsen, 2022).

Given these challenges, there is an urgent need for scalable, automated tools that can systematically organize and analyze factual claims. Taxonomies, which are hierarchical classification systems, can effectively organize content from broad to fine-grained categories, facilitating improved data navigation and understanding.

This need is underscored by several studies advocating for taxonomies to navigate the misinformation and factual claims landscape. For instance, researchers have categorized fake news into different types to better describe the phenomena (Tambini, 2017), constructed taxonomies for false information on social media to distinguish between opinion-based and fact-based content (Kumar and Shah, 2018), and proposed a taxonomy of misinformation on social media based on falsity level and evidence type (Zhao and Tsang, 2022).

In this thesis proposal, we introduce an automated framework for efficiently constructing a taxonomy of online factual claims. This framework leverages large language models (LLMs), incorporating learning examples curated by human experts under the guidance of LLMs. The framework groups semantically similar factual claims, identifies distinct ones, and arranges them into hierarchical taxonomies with broad, medium, and detailed categories. This structure is designed to help researchers and stakeholders gain a clearer understanding of the claims circulating online.

2 Research Objectives

The main objectives of this thesis are:

- **Automated Taxonomy Construction**: Design and implement an automated system that utilizes LLMs for constructing a taxonomy of factual claims. This system categorizes factual claims on social media into a structured format that enhances their verification and analysis.

- **Distinct Claim Identification**: Develop an effective method for identifying factual claims and eliminating redundancy by deduplicating repetitive content.

- **Evaluate Framework Effectiveness**: Assess the accuracy and efficiency of the framework using diverse social media datasets, ensuring it manages the variability and volume of data from these platforms.

LLMs possess extensive background knowledge that remains applicable as online content evolves, given that LLMs themselves adapt over time to reflect the latest information. By leveraging the advanced capabilities of LLMs and few-shot learning, the framework automates the labor-intensive task of organizing and categorizing claims while maintaining adaptability to the dynamic nature of social media discourse.

We address several challenges inherent in the framework. A primary challenge is the semantic variability of claims, where similar ideas are expressed in different ways, complicating categorization. Our framework tackles this by clustering similar claims and identifying distinct ones. Another challenge is ensuring the framework's scalability and applicability across various datasets and domains. To overcome this, we incorporate adaptable learning examples into the LLM prompt, making it easy to tailor the framework to different contexts. To demonstrate the generalizability of our approach, we conduct experiments on three distinct datasets, including posts from *X* and Facebook, covering topics such as COVID-19 vaccines, climate change, and cybersecurity.

The preliminary results of our experiments highlight the framework's effectiveness in organizing factual claims on social media. By identifying distinct factual claims, the framework significantly reduces redundancy, facilitating more efficient fact-checking processes. The hierarchical taxonomies generated allow for multi-level exploration of claims, enhancing the understanding of information at varying depths. Furthermore, the framework shows strong performance across datasets from different domains, demonstrating its adaptability and potential for broad application. Through this work, we aim to provide researchers, policymakers, and fact-checkers with an advanced tool for navigating the complex and evolving landscape of social media, fostering more informed and resilient public discourse.

3 Literature Review

Taxonomy construction has been extensively studied, though the definitions of the problems may vary. Generally, taxonomies are hierarchically structured classifications of concepts, terms, and entities that help users organize and navigate information (Carrion et al., 2019; Yang, 2012). Different domains and contexts impose varying requirements and preferences for taxonomy design and evaluation (Kundisch et al., 2021).

Generic taxonomy construction tasks typically involve short concept terms or entity names, often represented as hypernym-hyponym pairs. For example, CoRel (Huang et al., 2020) employs concept learning and relation transfer for seed-guided topical taxonomy construction, while TaxoGen (Zhang et al., 2018) utilizes term embeddings and hierarchical clustering to recursively build a topic taxonomy.

Constructing taxonomies from broader and less formal content, such as social media posts, differs significantly from generic taxonomy construction tasks. The inherent variability in such content makes it difficult to establish a gold-standard taxonomy. Several studies have attempted to address this challenge. For instance, Zamir and Etzioni (1998) explored automatic taxonomy generation from web document collections using clustering techniques, while Medelyan et al. (2013) leveraged knowledge sources such as Wikipedia, DBpedia, and Freebase, along with domain-specific taxonomies, to guide taxonomy construction. However, those methods often suffer from accuracy limitations or impose restrictions on input data.

The rise of deep learning and LLMs has expanded the potential of taxonomy construction. For example, Chen et al. (2020) employed pretrained language models to construct taxonomic trees (e.g., WordNet), while Chen et al. (2023) compared prompting and fine-tuning approaches for hypernym taxonomy construction. Additionally, Shah et al. (2023) introduced an end-to-end pipeline that integrates LLMs with a human-in-the-loop approach to generate, refine, and apply labels for user intent analysis in log data. These advancements inspire our efforts to tackle taxonomy construction for more informal data types, such as social media posts, and for more complex content, such as factual claims.

4 Methodology

To facilitate the analysis of social media landscapes, we propose a framework designed to automate the construction of a taxonomy for factual claims across different platforms. The framework starts with claim detection to identify check-worthy factual claims on social media, followed by the identification of distinct claims, and culminating in the construction the taxonomy of distinct claims. An overview of our framework is depicted in Figure 1.

4.1 Claim Detection

The social media data contains a wide range of content, including personal opinions, personal experiences, and entertainment. We integrate claim detection in the framework to identify posts likely containing factual claims, which may carry misinformation. Claim detection is well-documented, with one primary goal being to identify factual statements that need to be verified for their truthfulness (Zeng et al., 2021; Guo et al., 2022; Das et al., 2023). We employ ClaimBuster (Hassan et al., 2017), a pioneering model for detecting factual claims. This model assigns a score to each sentence or paragraph to indicate the likelihood of containing a check-worthy factual claim. According to Hassan et al. (2017), the task is defined based on the public's interest in knowing the truthfulness of the statements. Posts meet a certain threshold score were retained for further processing in the framework, thus refining our dataset to a subset more likely to contain relevant factual information for taxonomy construction.

4.2 Identifying Distinct Claims

The large volume of social media content includes a wide range of posts that are often repeated or rephrased. For example, the posts "*BREAKING: Pentagon rescinds COVID-19 vaccine mandate*" and "*The Pentagon officially rescinds COVID-19 vaccine mandate*" convey the same factual claim in different phrasing. To focus on unique claims, we first perform clustering to group identical or nearly identical factual claims. We utilize HDBSCAN (Campello et al., 2013) for clustering due to its efficacy in handling noise and detecting outliers, which is crucial for our datasets where many posts are unique and should be treated as individual clusters. By clustering similar claims, we consolidate redundant claims into a single representation, streamlining the process of taxonomy construction. Semantic meanings of each claim are captured using Sentence-BERT (Reimers, 2019) embeddings, providing dense vector representations.

After applying HDBSCAN clustering, we identify distinct claims by selecting the first post from each cluster, excluding those classified as outliers (*cluster -1*). These outliers represent less common content, whereas our focus is on frequently discussed factual claims, as these claims tend to attract more user attention. Additionally, users are more likely to believe information they encounter multiple times (Pennycook et al., 2018), suggesting that repeated claims hold greater significance. We avoid using centroids or other computationally intensive methods for selecting representative posts due to the high similarity within each cluster and the priority of efficiency. Each cluster represents a unique factual claim, forming the foundation of our taxonomy construction.

4.3 Taxonomy Construction

The ultimate goal of this thesis proposal is to develop a hierarchical taxonomy that organizes a collection of factual claims $\mathcal{C}$ into topics at multiple levels of granularity, from broad to fine-grained topics. The taxonomy uses a three-tiered structure, consisting of broad topic t_b, medium topic t_m, and detailed topic t_d for each claim, as shown on the right side of Figure 1 for the COVID-19 vaccine taxonomy. Such hierarchical structure ensures that the taxonomy captures both high-level themes and nuanced distinctions across factual claims. To automate the taxonomy construction process, we create learning examples that contain factual claims and their corresponding topics at various levels. These examples form an initial seed taxonomy that guides LLMs in expanding the topic coverage. The LLMs are prompted with the seed taxonomy and learning examples to generate topics for each distinct factual claim. Upon generating topics for all claims, we

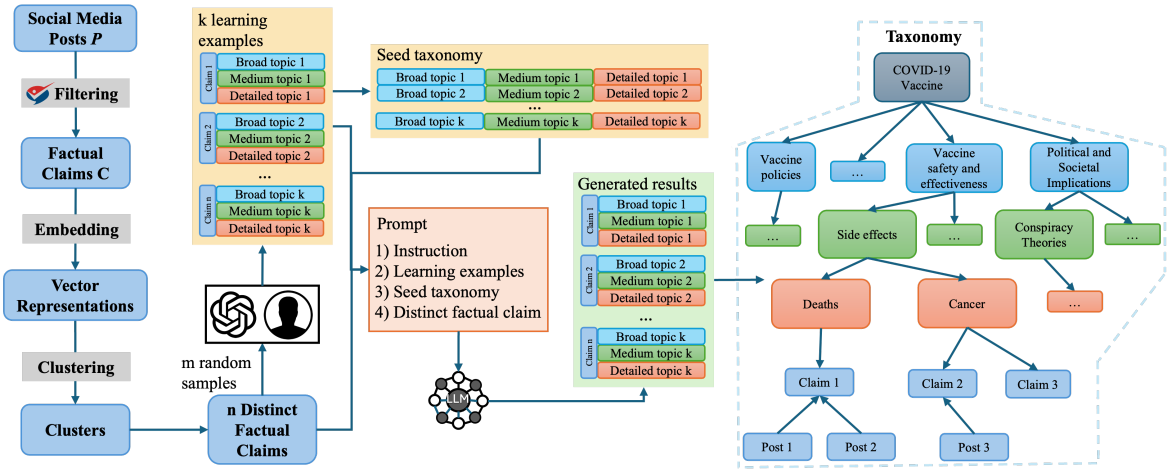

Figure 1: Taxonomy Construction Framework Overview.

consolidate these into the final taxonomy structure.

4.3.1 Creation of Seed Taxonomy and Learning Examples

Although LLMs hold general knowledge, they require specific guidance to generate hierarchical topics accurately. Our initial experiments reveal that LLMs sometimes produce inconsistent results, such as generating different topics for similar claims. To address this, we create a seed taxonomy from a sample of factual claims, providing a foundation for LLM expansion. The branches of the seed taxonomy are used as learning examples $\mathcal{L}$, which serve as in-context learning references for the LLMs, helping control the number and variation of generated topics. These examples demonstrate how to structure topics across different granularity levels for various claims. To create these examples, we select a random subset of distinct claims $\{c_1, c_2, \ldots, c_m\} \subset \mathcal{C}$, denoted as $\mathcal{R}$, for annotation. Direct human annotation for each claim is time-consuming and challenging, as it requires annotations to be concise, accurate, and consistent. Therefore, we leverage the power of LLM, specifically ChatGPT, [1] to assist in generating topics for selected claims. We first prompt ChatGPT with a target claim and instruct it to generate topics for the claim at three levels of granularities: broad, medium, and detailed. After evaluating the generated topics, we make necessary adjustments and annotate each claim with $\{t^b, t^m, t^d\}$. The LLM-guided annotation minimizes manual effort while allowing for customization based on user requirements. Below is an example of the prompt used for the COVID-19 vaccine dataset:

```
 You will be given a tweet related to
COVID-19 vaccine.  Please generate topics for
the tweet from different granularities such as
broad topic, medium topic, and detailed topic.
Each generated topic should be no more than
eight words and you should minimize the number
of topics generated.
```

To ensure consistency and limit topic variation, we minimize the number and topics and assign the same topics to claims that fit within the same category. After annotating all selected m factual claims, we scrutinize the top q frequent broad topics and identify the representative topic sets. The final set of k factual claims, along with their corresponding broad, medium, and detailed topics, are used as learning examples $\mathcal{L}$.

4.3.2 Topic Generation

To automate the taxonomy construction process and reduce human effort, we employed two LLMs, Zephyr (Tunstall et al., 2023) and GPT-4o mini, [2] to generate a set of broad topic, medium topic, and detailed topic, denoted as $\{t^b, t^m, t^d\}$, for each factual claim $c \in \mathcal{C}$. Zephyr is selected for its competitive performance in language understanding tasks among all 7-billion-parameter LLMs (Chiang et al., 2024), while GPT-4o mini is chosen for its balance of cost-efficiency and performance.

The learning examples described in Section 4.3.1 are utilized as part of the prompt for the LLMs. The prompt consists of $c_i \in \mathcal{L}$, all the annotated $\{t^b, t^m, t^d\}$ sets of $\mathcal{L}$ (i.e., seed taxonomy), the

[1]https://chatgpt.com/

[2]https://openai.com/index/gpt-4o-mini-advancing-cost-efficient-intelligence/

Dataset	Claim	Broad Topic	Medium Topic	Detailed Topic
COVID-19 Vaccine	John Stockton boldly suggests 'thousands' of pro athletes died after Covid vaccine shot https://t.co/nXbt6Apm2q via @marca	Vaccine Safety and Effectiveness	Vaccine Side Effects	Vaccine-Related Injuries and Deaths
COVID-19 Vaccine	A lot of people in 'stage 4 cancer' after #Covid #Vaccine https://t.co/z0YAqGgQrL	Vaccine Safety and Effectiveness	Vaccine Side Effects	Cancer Side Effect
Climate Change	Climate change is an existential threat to humanity. On Earth Day and every day, we remain committed to taking the most aggressive climate action ever.	Activism and Public Awareness	Climate Advocacy	Aggressive Climate Action
Climate Change	Climate change causes Dry spell in Kashmir, The weather in Kashmir is warmer than Delhi and Chandigarh, No snow rain in Kashmir During Chillai Kalan	Environmental Impact	Global Warming	Climate Change Effects in Kashmir
Cybersecurity	CBN Exempts 16 Items from Cybersecurity Levy...including Salary, Loans, Pension, Donations	Policies and Governance	Government Regulations	Cybersecurity Levy Exemptions
Cybersecurity	Streaming giant Roku has recently been targeted by a pair of cyberattacks, and the company confirmed over a half million Roku accounts were compromised.	Threats	Cyberattacks	Roku Account Compromise

Table 1: Factual Claims and Their Topics Generated by GPT-4o mini in Different Datasets

question that asks LLMs to produce broad, medium, and detailed topics for c_i, and the answer to the question (i.e., corresponding $\{t_i^b, t_i^m, t_i^d\}$ of c_i). After the LLMs learns from the k examples, it is provided with an unseen claim c_j and asked to generate topics $\{\hat{t_j^b}, \hat{t_j^m}, \hat{t_j^d}\}$ for c_j. Due to the limited context length of the LLMs, one prompt generates $\{\hat{t_j^b}, \hat{t_j^m}, \hat{t_j^d}\}$ for only one c_j. This generation process is iterated until finishing generating $\{\hat{t_j^b}, \hat{t_j^m}, \hat{t_j^d}\}$ for all $c_j \in \mathcal{C}$. The prompt is detailed in Figure 2 in Appendix A.

4.3.3 Taxonomy Construction

After the LLMs generates the topics for each claim, we consolidate the results to construct the taxonomy. Medium topics that share the same broad topic are considered child nodes of that broad topic, and detailed topics are similarly considered child nodes of their respective medium topics. For example, if one claim has "*Broad Topic: Vaccine Safety and Effectiveness; Medium Topic: Vaccine Side Effects*" and another claim has "*Broad Topic: Vaccine Safety and Effectiveness; Medium Topic: Vaccine Injury*," then "Vaccine Side Effects" and "Vaccine Injury" are two child nodes of "Vaccine Safety and Effectiveness." In this way, a complete taxonomy can be constructed based on the generated topics.

5 Experiments and Results

We apply our framework to three distinct datasets covering different domains: COVID-19 vaccine, climate change, and cybersecurity. By leveraging clustering and distinct claim identification, we significantly reduce the redundancy within each dataset, ensuring a more concise and representative taxonomy. We have conducted preliminary experiments to evaluate the effectiveness and accuracy of LLM-generated topics for factual claims. Table 1 presents sample results produced by GPT-4o mini across the three datasets. The generated topics demonstrate strong semantic relevance to the claims while maintaining a well-structured hierarchical organization, aiding in efficient data exploration. Overall, the results indicate promising performance of LLM-generated taxonomies, highlighting their potential for scalable and automated factual claim categorization.

6 Conclusion and Future Work

This thesis proposal has presented a novel framework for structuring the overwhelming influx of information on social media. By leveraging LLMs, our approach enhances the efficiency of categorizing factual claims while addressing the urgent need for scalable and automated solutions in analyzing online discourse. The results from diverse datasets indicates that our framework can adapt to different contexts and maintain accuracy in identifying and organizing factual claims. The generated hierarchical taxonomies can simplify the complexity of social media discourse, enabling stakeholders from various fields to navigate and analyze data more efficiently. Despite the promising results, further work is required to refine the evaluation of the generated taxonomy. A key priority is the development of robust evaluation metrics to systematically assess the accuracy, coherence, and usability of the topic hierarchies. Future research will focus on further refining the adaptability of the framework, exploring the integration of more advanced machine learning techniques. Additionally, enhancing real-time processing capabilities will be crucial for enabling dynamic updates to taxonomies in response to emerging information.

References

Hunt Allcott, Matthew Gentzkow, and Chuan Yu. 2019. Trends in the diffusion of misinformation on social media. *Research & Politics*, 6(2):2053168019848554.

Diana Leigh Amundsen. 2022. Using digital content analysis for online research: Online news media depictions of older adults.

Ricardo JGB Campello, Davoud Moulavi, and Jörg Sander. 2013. Density-based clustering based on hierarchical density estimates. In *Pacific-Asia conference on knowledge discovery and data mining*, pages 160–172. Springer.

Ana Isabel Canhoto and Yuvraj Padmanabhan. 2015. 'we (don't) know how you feel'–a comparative study of automated vs. manual analysis of social media conversations. *Journal of Marketing Management*, 31(9-10):1141–1157.

Belen Carrion, Teresa Onorati, Paloma Díaz, and Vasiliki Triga. 2019. A taxonomy generation tool for semantic visual analysis of large corpus of documents. *Multimedia Tools and Applications*, 78:32919–32937.

Boqi Chen, Fandi Yi, and Dániel Varró. 2023. Prompting or fine-tuning? a comparative study of large language models for taxonomy construction. In *2023 ACM/IEEE International Conference on Model Driven Engineering Languages and Systems Companion (MODELS-C)*, pages 588–596. IEEE.

Catherine Chen, Kevin Lin, and Dan Klein. 2020. Constructing taxonomies from pretrained language models. *arXiv preprint arXiv:2010.12813*.

Wei-Lin Chiang, Lianmin Zheng, Ying Sheng, Anastasios Nikolas Angelopoulos, Tianle Li, Dacheng Li, Hao Zhang, Banghua Zhu, Michael Jordan, Joseph E. Gonzalez, and Ion Stoica. 2024. Chatbot arena: An open platform for evaluating llms by human preference. *Preprint*, arXiv:2403.04132.

Anubrata Das, Houjiang Liu, Venelin Kovatchev, and Matthew Lease. 2023. The state of human-centered nlp technology for fact-checking. *Information processing & management*, 60(2):103219.

Michela Del Vicario, Alessandro Bessi, Fabiana Zollo, Fabio Petroni, Antonio Scala, Guido Caldarelli, H Eugene Stanley, and Walter Quattrociocchi. 2016. The spreading of misinformation online. *Proceedings of the national academy of Sciences*, 113(3):554–559.

Zhijiang Guo, Michael Schlichtkrull, and Andreas Vlachos. 2022. A survey on automated fact-checking. *Transactions of the Association for Computational Linguistics*, 10:178–206.

Naeemul Hassan, Fatma Arslan, Chengkai Li, and Mark Tremayne. 2017. Toward automated fact-checking: Detecting check-worthy factual claims by claimbuster. In *Proceedings of the 23rd ACM SIGKDD international conference on knowledge discovery and data mining*, pages 1803–1812.

Kristina Hook and Ernesto Verdeja. 2022. Social media misinformation and the prevention of political instability and mass atrocities. *online], https://www. stimson. org/2022/social-media-misinformation-and-the-prevention-of-politicalinstability-and-mass-atrocities*.

Jiaxin Huang, Yiqing Xie, Yu Meng, Yunyi Zhang, and Jiawei Han. 2020. Corel: Seed-guided topical taxonomy construction by concept learning and relation transferring. In *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, pages 1928–1936.

Srijan Kumar and Neil Shah. 2018. False information on web and social media: A survey. *arXiv preprint arXiv:1804.08559*.

Dennis Kundisch, Jan Muntermann, Anna Maria Oberländer, Daniel Rau, Maximilian Röglinger, Thorsten Schoormann, and Daniel Szopinski. 2021. An update for taxonomy designers: methodological guidance from information systems research. *Business & Information Systems Engineering*, pages 1–19.

Olena Medelyan, Steve Manion, Jeen Broekstra, Anna Divoli, Anna-Lan Huang, and Ian H Witten. 2013. Constructing a focused taxonomy from a document collection. In *The Semantic Web: Semantics and Big Data: 10th International Conference, ESWC 2013, Montpellier, France, May 26-30, 2013. Proceedings 10*, pages 367–381. Springer.

Patricia Moravec, Randall Minas, and Alan R Dennis. 2018. Fake news on social media: People believe what they want to believe when it makes no sense at all. *Kelley School of Business research paper*, (18-87).

Sadiq Muhammed T and Saji K Mathew. 2022. The disaster of misinformation: a review of research in social media. *International journal of data science and analytics*, 13(4):271–285.

Jingwei Ni, Minjing Shi, Dominik Stammbach, Mrinmaya Sachan, Elliott Ash, and Markus Leippold. 2024. Afacta: Assisting the annotation of factual claim detection with reliable llm annotators. *arXiv preprint arXiv:2402.11073*.

Katherine Ognyanova, David Lazer, Ronald E Robertson, and Christo Wilson. 2020. Misinformation in action: Fake news exposure is linked to lower trust in media, higher trust in government when your side is in power. *Harvard Kennedy School Misinformation Review*.

Gordon Pennycook, Tyrone D Cannon, and David G Rand. 2018. Prior exposure increases perceived accuracy of fake news. *Journal of experimental psychology: general*, 147(12):1865.

N Reimers. 2019. Sentence-bert: Sentence embeddings using siamese bert-networks. *arXiv preprint arXiv:1908.10084*.

Chirag Shah, Ryen W White, Reid Andersen, Georg Buscher, Scott Counts, Sarkar Snigdha Sarathi Das, Ali Montazer, Sathish Manivannan, Jennifer Neville, Xiaochuan Ni, et al. 2023. Using large language models to generate, validate, and apply user intent taxonomies. *arXiv preprint arXiv:2309.13063*.

Victor Suarez-Lledo and Javier Alvarez-Galvez. 2021. Prevalence of health misinformation on social media: systematic review. *Journal of medical Internet research*, 23(1):e17187.

Damian Tambini. 2017. Fake news: public policy responses.

Tuuli Toivonen, Vuokko Heikinheimo, Christoph Fink, Anna Hausmann, Tuomo Hiippala, Olle Järv, Henrikki Tenkanen, and Enrico Di Minin. 2019. Social media data for conservation science: A methodological overview. *Biological Conservation*, 233:298–315.

Lewis Tunstall, Edward Beeching, Nathan Lambert, Nazneen Rajani, Kashif Rasul, Younes Belkada, Shengyi Huang, Leandro von Werra, Clémentine Fourrier, Nathan Habib, Nathan Sarrazin, Omar Sanseviero, Alexander M. Rush, and Thomas Wolf. 2023. Zephyr: Direct distillation of lm alignment. *Preprint*, arXiv:2310.16944.

Liang Wu, Fred Morstatter, Kathleen M Carley, and Huan Liu. 2019. Misinformation in social media: definition, manipulation, and detection. *ACM SIGKDD explorations newsletter*, 21(2):80–90.

Xizhu Xiao, Porismita Borah, and Yan Su. 2021. The dangers of blind trust: Examining the interplay among social media news use, misinformation identification, and news trust on conspiracy beliefs. *Public Understanding of Science*, 30(8):977–992.

Hui Yang. 2012. Constructing task-specific taxonomies for document collection browsing. In *Proceedings of the 2012 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning*, pages 1278–1289.

Oren Zamir and Oren Etzioni. 1998. Web document clustering: A feasibility demonstration. In *Proceedings of the 21st annual international ACM SIGIR conference on Research and development in information retrieval*, pages 46–54.

Xia Zeng, Amani S Abumansour, and Arkaitz Zubiaga. 2021. Automated fact-checking: A survey. *Language and Linguistics Compass*, 15(10):e12438.

Chao Zhang, Fangbo Tao, Xiusi Chen, Jiaming Shen, Meng Jiang, Brian Sadler, Michelle Vanni, and Jiawei Han. 2018. Taxogen: Unsupervised topic taxonomy construction by adaptive term embedding and clustering. In *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, pages 2701–2709.

Haiqi Zhang, Zhengyuan Zhu, Zeyu Zhang, Jacob Devasier, and Chengkai Li. 2024. Granular analysis of social media users' truthfulness stances toward climate change factual claims. In *Proceedings of the 1st Workshop on Natural Language Processing Meets Climate Change (ClimateNLP 2024)*, pages 233–240.

Xinyan Zhao and Stephanie Tsang. 2022. How people process different types of misinformation on social media: A taxonomy based on falsity level and evidence type. *Available at SSRN 4259593*.

Cangqi Zhou, Qianchuan Zhao, and Wenbo Lu. 2015. Impact of repeated exposures on information spreading in social networks. *PloS one*, 10(10):e0140556.

A Prompt for Topic Generation

There are k learning examples used to guide the LLM in generating a broad topic, a medium topic, and a detailed topic for each factual claim, as shown in Figure 2. Each prompt example contains a factual claim, seed taxonomy (i.e., a list of topic sets from the k annotated factual claims), a question asking the LLM to generate broad, medium, and detailed topics for the claim, and the answer to the question. In the question, the LLM is instructed to prioritize generating topics from the existing topics. If none of the existing topics align well with the claim, the LLM is then directed to generate new topics. This instruction ensures that the LLM produces a limited number of topics. This prompt is iterated through all the factual claims to generate topics for them.

LLM Input

Q: You will be given a claim related to COVID-19 vaccine. Please generate topics for the claim from different granularities such as broad topic, medium topic, and detailed topic. Each generated topic should be no more than eight words.
Here is a list of existing topics:
1. Broad topic: Government Policies; Medium topic: Vaccine Mandates; Detailed topic: Opposition to Vaccine Mandates;
2. Broad topic: Government Policies; Medium topic: Vaccine Policies; Detailed topic: Vaccine Privacy;
3. Broad topic: Vaccine Safety and Effectiveness; Medium topic: Vaccine Side Effects; Detailed topic: Vaccine-Related Injuries and Deaths;

...
k. ...
Please try to generate topics for the claim using existing topics. If there is no good match, then generate new topics following the same format.
Here is the claim: $<\mathbf{c}_i>$
A: Broad topic: $<\mathbf{t}^{\mathbf{b}}_i>$; Medium topic: $<\mathbf{t}^{\mathbf{m}}_i>$; Detailed topic: $<\mathbf{t}^{\mathbf{d}}_i>$

Q: ...
A: ...
...
Q: ...
A: ...

Q: You will be given a claim related to COVID-19 vaccine. Please generate topics for the claim from different granularities such as broad topic, medium topic, and detailed topic. Each generated topic should be no more than eight words.
Here is a list of existing topics:
1. Broad topic: Government Policies; Medium topic: Vaccine Mandates; Detailed topic: Opposition to Vaccine Mandates;
2. Broad topic: Government Policies; Medium topic: Vaccine Policies; Detailed topic: Vaccine Privacy;
3. Broad topic: Vaccine Safety and Effectiveness; Medium topic: Vaccine Side Effects; Detailed topic: Vaccine-Related Injuries and Deaths;
...
k. ...
Please try to generate topics for the claim using existing topics. If there is no good match, then generate new topics following the same format.
Here is the claim: $<\mathbf{c}_j>$

LLM Output

A: Broad topic: $<\mathbf{t}^{\mathbf{b}}_j>$; Medium topic: $<\mathbf{t}^{\mathbf{m}}_j>$; Detailed topic: $<\mathbf{t}^{\mathbf{d}}_j>$

Figure 2: Prompt Used to Guide LLMs in Generating Claim Topics