



AMICA: Alleviating Misinformation for Chinese Americans

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ABSTRACT

The increasing popularity of social media promotes the proliferation of misinformation, especially in the communities of Chinese-speaking diasporas, which has caused significant negative societal impacts. In addition, most of the existing efforts on misinformation mitigation have focused on English and other western languages, which makes numerous overseas Chinese a very vulnerable population to online disinformation campaigns. In this paper, we present AMICA, an information retrieval system for alleviating misinformation for Chinese Americans. AMICA dynamically collects data from popular social media platforms for Chinese Americans, including WeChat, Twitter, YouTube, and Chinese forums. The data are stored and indexed in Elasticsearch to provide advanced search functionalities. Given a user query, the ranking of social media posts considers both topical relevance and the likelihood of being misinformation.

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1 INTRODUCTION

Chinese Americans, a rapidly growing group in the US electorate, rely heavily on information in their native language. However, the Chinese media sphere in the US has been neglected, and questionable content has gained popularity among Chinese-speaking immigrants. Concerns have been raised about disinformation and polarization campaigns targeting US-based Chinese language speakers [10]. The distribution and consumption of misinformation are further complicated by differences in values, interests, and communication systems.

In this paper, we present AMICA, an information retrieval system for Alleviating Misinformation for Chinese Americans. AMICA is a repository and monitor that stores and ranks Chinese language posts from social media and web forums, making it easier to search for disinformation and misinformation. The data is indexed in Elasticsearch for advanced search functionalities. The ranking of social media posts considers both relevance and likelihood of misinformation when responding to user queries. AMICA can aid newsrooms, journalists, and anti-disinformation initiatives in capturing emerging disinformation topics and propagation patterns, and prepare for future reporting. The system can be used as labeled training data for research efforts on disinformation. To the best of our knowledge, there exists no prior work on developing an information retrieval system for combating misinformation for overseas Chinese.

CCS CONCEPTS

• Information systems → Information extraction; • Computing methodologies → Natural language processing.

KEYWORDS

Chinese misinformation, Social media, Information retrieval

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2 RELATED WORK

Over the past few years, the Chinese-language based misinformation propagation in online social media, including topics on COVID, Ukraine war, the political tensions between U.S. and China, etc., has attracted extensive attention [1, 2, 5, 17]. In [6], the authors observed 18 Chinese-based propaganda techniques. Although some of these techniques are propaganda-specific, there are some techniques that can be effective for general misinformation propagation and are adopted in this study. In [19], the authors identify that WeChat, a Chinese-language based social media platform, provides

key clues to how misinformation is constructed and distributed among the Chinese-American community.

Many existing studies have revealed the unique propagation patterns of misinformation in online social media [3, 11, 16, 20], which can serve as effective indicators for learning schemes to detect misinformation. However, very few studies are exploring misinformation propagation patterns in the Chinese-language context. In addition, due to the challenge of data collection, there are limited data sets containing fine-grained temporal information to reflect the dynamic evolution of propagation data. In this study, we adopt a dynamic data crawling approach, which can well balance the trade-off between data collection costs and granularity of the propagation data.

Beyond academia research, there are ongoing efforts from practitioners. For example, Google's Fact Check Explorer¹ is a search engines where users can search for potential misinformation articles, while it does not support Chinese language. Piyaoba² is a non-profit fact-checking portal to combat misinformation and disinformation directed at the Chinese American community, and they rely on domain experts to manually identify and debunk misinformation posts from social media.

3 SYSTEM DESIGN

AMICA is a web-based search engine that allows users to search for information by entering keywords or phrases. It returns a list of relevant results based on the user's query. The results are ranked by taking into account various factors such as relevance, sentiment, and propagation data. Its backend includes crawlers to collect data, Elasticsearch³ for storage, and two ranking scores (topical relevance and machine learning-based misinformation likelihood) are combined to present results to the user. The major components and pipeline of AMICA are shown in Figure 1.

3.1 User Interface

The frontend of AMICA is a web search page built with Flask [9], a lightweight Python web framework, that allows users to search for information on it. The user interface of the web search page is built using HTML, CSS, and JavaScript, and can be customized to provide a user-friendly experience.

AMICA has a secure login system that allows authorized users to access the search engine and conduct searches. Once logged in, users can enter search queries into a search box, view results on the page, and interact with the results in several ways, including clicking on links and filtering results based on other criteria. Search results typically include the essential information about the post, such as the post headline, author, first published date, etc. To improve the user experience, each search result includes a preview on the page. Screenshots of the frontend are included in Section 4.

3.2 Data Scraping

AMICA integrates social media data from Twitter, YouTube, WeChat, and Chinese forums. We automatically crawl the data from Twitter and YouTube with their official APIs and from WeChat with an

open-source program. We collect articles, posts, and transcripts from monitored accounts and regularly obtain propagation data, such as reads and views, to analyze misinformation spread. Monitored accounts are identified manually and from reports by Chinese-language fact-checking organizations [14]. Our data collection program uses four crawler instances and stores data in Elasticsearch for convenient querying and modification by APIs.

Twitter: We collect data using the Twitter official API [18], which regularly monitors target accounts, captures newly posted data, and stores them in the proposed repository. Data includes basic account and tweet information, as well as propagation data such as likes, retweets, and comments, with collection frequency and duration to be discussed at the end of this section.

YouTube: We utilize Google developer accounts and the YouTube API V3 [8] to collect basic information about YouTube accounts and videos, including user name, user id, video id, title, description, URL, transcript (if available), and published date, as well as propagation data similar to the Twitter data, and their corresponding time stamps, following the settings of our dynamic crawling mechanism.

WeChat: Being a "closed" system, WeChat lacks an official API for data collection. Thus we use an open source program called WeChat Spider [12] that captures communication data via a proxy between the server and user app, which requires logging into WeChat on a phone or emulator and using JavaScript code to collect data on targeted articles or profile pages. Due to WeChat's detection and blocking of crawling behavior, data collection is limited in speed, frequency, and duration. Therefore, we mainly focus on collecting basic information such as account name, published articles, dates, headlines, full text, and the number of reads with timestamps.

Bulletin-based Chinese Forums: We collect data from Chinese bulletin-based forums, such as WenXue City⁴ and Huaren.us⁵, using our own web crawler based on Selenium [15], a web crawling tool. The collected data includes account name, article headline, full text, read number, replies number, URL, and published date.

Dynamic Crawling: We balance accuracy and collection costs by carefully designing the frequency of data crawling for propagation data (e.g., likes, retweets), due to limited API calls allowed by social media platforms. We observe a bursty human dynamics pattern where most propagation occurs within 24 hours of post publication, with few changes after 72 hours. Thus, we use a dynamic crawling window, with high frequency in the first 24 hours and low frequency from 24 to 72 hours.

3.3 Text Pre-processing

To enable further analysis, the posts undergo text normalization, tokenization, and part-of-speech (POS) tagging to assign labels such as verbs or nouns. In this stage, stopwords are also removed to improve the efficiency of the process and reduce noise in the data. To facilitate the two ranking systems employed in AMICA, different analyzers are used in this process as described below.

The Smart Chinese Analysis plugin (*smartcn*)⁶ is used in Elasticsearch built-in ranking system to enhance the search engine's

¹<https://toolbox.google.com/factcheck/explorer>

²<https://www.piyaoba.org/>

³<https://github.com/elasticsearch/elasticsearch>

⁴<https://www.wenxuecity.com/>

⁵<https://huaren.us/home/index>

⁶<https://www.elastic.co/guide/en/elasticsearch/plugins/current/analysis-smartcn.html>

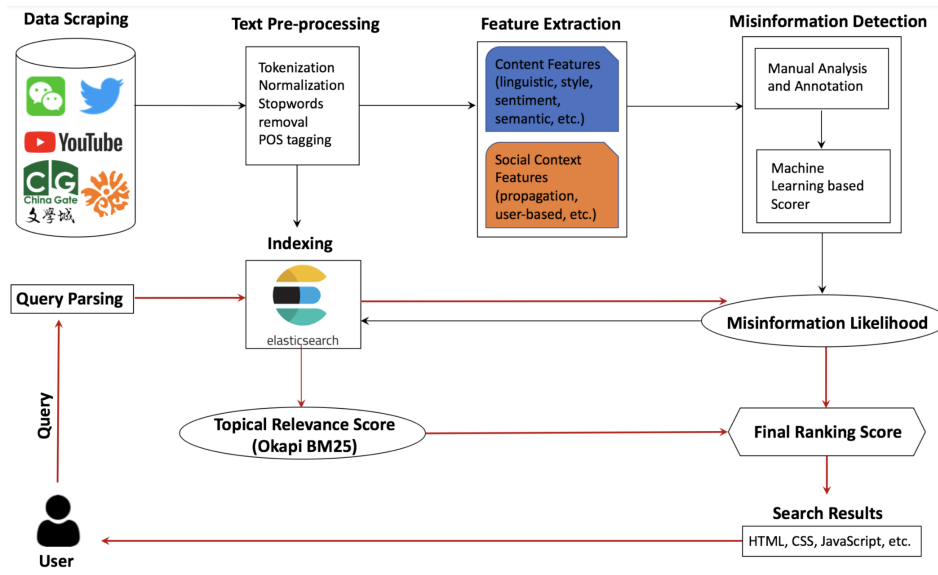


Figure 1: The pipeline of AMICA with the major components. The black arrows represent offline computation before a query is given and the red arrows indicate online processing when a user query is issued at run time.

performance on Chinese texts. This plugin is designed specifically for the Chinese language and improves the engine’s understanding of Chinese words, resulting in more accurate and relevant search results for users.

For Chinese text segmentation, *Jieba*⁷, a Chinese text analysis package in Python is utilized, which uses a dictionary-based approach to tokenize Chinese texts into words and phrases. It also supports part-of-speech tagging and keyword extraction. After text pre-processing the text data, Elasticsearch indexes each post according to a mapping property that has been predefined (i.e. Okapi BM25). This mapping property specifies the structure of the data and how it will be stored and searched, allowing for fast and efficient retrieval of information when queried.

3.4 Feature Extraction

To determine if a post contains misinformation, the following features are extracted by AMICA:

Content Features: which measures textual characteristics of the content, including 1) the min-max normalize length of the post; 2) the number of question marks, as multiple questions in a post, often used in user posts invoking worry or concern; 3) the number of exclamation marks, as many exclamation marks are used for attention-grabbing language, often seen in user generated content posts seeking attention; 4) strong attempts to gather attention by using language that stokes fear, anxiety, worry, or shock, often seen in posts with exclamation marks in quick succession. Examples (translated) include *Shocking!*, *Disappointed!*, *OMG!*, *Warning!*, *WHAT!*, *Rarely seen in history!*, etc.; 5) the sentiment of a post, which can be determined using natural language processing techniques. The package *cnntext* [7] is leveraged to perform Chinese text analysis using traditional methods such as word count and sentiment analysis. In order to extract attention-gathering features, a pre-defined

⁷<https://github.com/fxsjy/jieba>

dictionary containing commonly used attention-gathering words is utilized.

Social Context Features: which measures social characteristics of the post, including 1) where the post was originally published; 2) how the post has spread or propagated, such as the number of likes, shares/retweets, or comments, and how quickly it has spread; 3) sharing evidence or references to support claims by citing other sources.

3.5 Misinformation Detection

To measure the likelihood of a given post being misinformation, we deploy a machine learning approach. Specifically, we used the logistic regression model [4] by taking the features discussed in the previous section as input and generating a score by the Sigmoid function indicating the probability that the content is misinformation. To create training data for the model, two domain experts manually labeled posts from the social media platforms that we monitored. We randomly sampled posts from the entire corpus and treated them as non-misinformation since most of the posts in the corpus are legitimate content. In the ongoing work, we are utilizing the known misinformation posts manually identified by some Chinese fact-checking websites such as Piyaoba as part of the training data. We are also experimenting with more advanced machine learning models as more training data are accumulated. It is worth noting that the misinformation likelihood is query independent. Once the model is trained, we calculate the misinformation likelihood for all the posts in the corpus offline and store them in the Elasticsearch database, which will be later combined with the topical relevance to generate the final ranking given a query.

3.6 Ranking

For a given query, the final ranking score of a post combines topical relevance (query-dependent) with misinformation likelihood



Figure 2: Screenshot of the AMICA result page with results based on the search criteria with the query “移民 (immigrants)” in the post headline.

(query-independent) introduced in Section 3.5. We used the Elastic-search built-in Okapi BM25 [13] to measure the topical relevance, factoring in term frequency and document length. The posts on different social media platforms may have different characteristics. For example, tweets on Twitter are usually much shorter than an article on WeChat, which may result in BM25 scores of different ranges across platforms. To make all the scores (both in BM25 and misinformation likelihood) comparable, we use min-max normalization to normalize the scores within each respective social platform. The posts/articles are then ranked based on the descending order of the sum of BM25 and misinformation likelihood scores. The frontend will render the page based on this result.

4 DEMONSTRATION

In this section, we briefly demonstrate the main functionalities of AMICA. As illustrated in Figure 2, the search criteria bar is located at the top of the page allows users to enter their queries and search based on various parameters including post headline, post full text, site/platform name, and author name. Users can further refine their search results based on the publication date of each post. The search results are displayed using Bootstrap⁸ cards, and the total number of results is indicated above the result cards.

Each result card shown in Figure 3 contains basic information about a post, as well as its topic relevance score and misinformation likelihood, with a logo on the top left corner indicating the original platform or media where the post was published. In addition, there is a button for more details that opens a pop-up window displaying a line chart for propagation data, showing how the post has spread over time, and other information about the post. There is also a button for human review, which allows users to submit a review form to determine whether the post is misinformation or not. The review will be stored in an Elasticsearch database, and each user can only submit one review per post. This feature helps improve the accuracy of the misinformation likelihood score, as it enables human experts to verify whether a post is actually misinformation or not. We also have a button that allows users to view other users’ reviews in the database for the same post. Due to the space limit, we skip the screenshot for those three buttons.

As of this writing, AMICA is monitoring 119 accounts on Twitter (85), WeChat (11), and YouTube (23), with a total of 163,930 records in our database. Twitter has the highest number of records at 158,240, followed by WeChat with 3,065 and YouTube with 2,625. The numbers are growing every day as data are being constantly collected.

⁸https://getbootstrap.com/

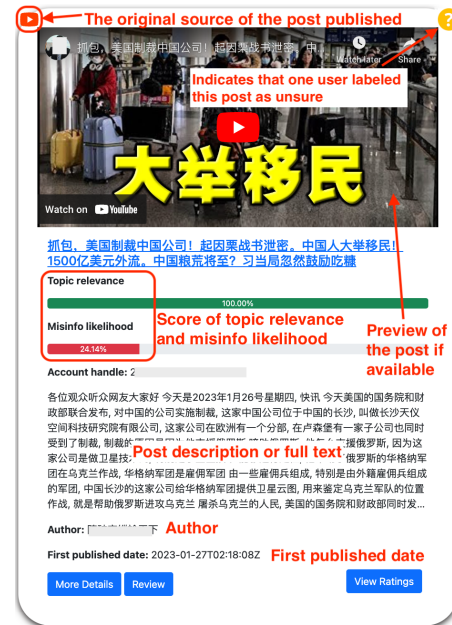


Figure 3: Screenshot of one example result card.

5 CONCLUSION AND FUTURE WORK

AMICA is a search engine designed to counter misinformation. It includes a backend system that utilizes a web crawler, database, and machine learning model to score data and provide users with relevant search results. The frontend is a web search page built with Flask and features a secure login system for authorized users. AMICA is currently being tested with real-world users, and we are continuously improving it based on user feedback. As data accumulate, we plan to leverage advanced IR/NLP/ML techniques to improve accuracy and scalability of the system.

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