Identifying and Characterizing Active Citizens who Refute Misinformation in Social Media

Yida Mu
The University of Sheffield
Sheffield, UK
y.mu@sheffield.ac.uk

Pu Niu
Central China Normal University
Wuhan, China
nphenu@126.com

Nikolaos Aletras
The University of Sheffield
Sheffield, UK
n.aletras@sheffield.ac.uk

ABSTRACT
The phenomenon of misinformation spreading in social media has developed a new form of active citizens who focus on tackling the problem by refuting posts that might contain misinformation. Automatically identifying and characterizing the behavior of such active citizens in social media is an important task in computational social science for complementing studies in misinformation analysis. In this paper, we study this task across different social media platforms (i.e., Twitter and Weibo) and languages (i.e., English and Chinese) for the first time. To this end, (1) we develop and make publicly available a new dataset of Weibo users mapped into one of the two categories (i.e., misinformation posters or active citizens); (2) we evaluate a battery of supervised models on our new Weibo dataset and an existing Twitter dataset which we repurpose for the task; and (3) we present an extensive analysis of the differences in language use between the two user categories.†

KEYWORDS
Social Media, Misinformation, Computational Social Science

1 INTRODUCTION
The diffusion of misinformation in social media has far-reaching implications on society (e.g., political polarization, election manipulation). Misinformation propagates faster than credible information among users in social media [67], whilst coming across a non-factual story once, it is enough to increase later perception of its accuracy [42].

To combat misinformation, several fact-checking platforms (e.g., Snopes2 and the Weibo Rumour Reporting Platform3) have been created with the aim to provide evidence on why particular claims are not factually correct (i.e., debunking or fact checking). This has subsequently resulted in a new form of active citizenship with large number of social media users directly reporting suspicious posts or actively sharing posts with evidence to refute claims made by other users which are likely to contain misinformation. Other examples of active citizenship include civic engagement, political activism, community help, volunteering and neighborhood associations [23]. In scope of social media, we consider users who actively debunk misinformation as active citizens since they work to make a difference (i.e., debunking misinformation) in online communities (e.g., social media platforms).

Automatically identifying and analyzing the behavior of active citizens in social networks is important for diffusion of misinformation prevention at the user level [13, 47, 54]. It can be used by (1) social media platforms (e.g., Facebook4) to track suspicious posts at an early stage (e.g., reports of suspicious posts from end users); (2) psychologists to complement studies on analyzing personality traits of those users who spread or debunk unreliable posts [43, 44]; and (3) fact-checking websites to develop personalized recommendation systems to assist active citizens in correcting suspicious posts [24, 63, 74].

Previous work on automatically identifying active citizens who refute misinformation has focused only on a single social media platform (i.e., Twitter) using a relatively small dataset (e.g., with only 454 users) consisting of users tweeting in English [13]. In addition, most of these previous studies have used supervised machine learning models with features extracted from text (e.g., bag-of-words, topics, psycho-linguistic information) and task-specific neural models trained from scratch without exploring state-of-the-art pretrained large language models [12].

The purpose of this paper is to study the differences in language use between the two user categories: (i) users who share suspicious posts (i.e., misinformation posters) and (ii) users who actively debunk misinformation (i.e., active citizens) To this end, we pose the following two research questions:

- Can we automatically identify active citizens and misinformation posters based on their language use in social media?
- Can we characterize the linguistic differentiation between the two groups of users?

To answer these research questions:

- We develop a new large publicly available dataset from Weibo consisting of 48,334 users labeled either as active citizens or misinformation posters;

† Pu Niu is the corresponding Author
2 Data is available here: https://github.com/YIDAMU/Misinfo_Debunker_and_Spreader
3 https://www.snopes.com/
4 http://service.account.sina.com

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.

WebSci ’22, June 26–29, 2022, Barcelona, Spain
© 2022 Association for Computing Machinery.
ACM ISBN 978-1-4503-9191-7/22/06 $15.00
https://doi.org/10.1145/3501247.3531559

4 https://www.facebook.com/journalismproject/programs/third-party-fact-checking/how-it-works
• We repurpose an existing dataset developed by Vo and Lee [64] to model the task of predicting active citizens and misinformation posters on Twitter;
• We evaluate several state-of-the-art pretrained neural language models adapted to the task. Due to the fact that the user text can be very long (e.g., thousands of posts), we develop efficient hierarchical transformer-based networks achieving up to 85.1 and 80.2 macro F1 scores on Weibo and Twitter respectively;
• We finally provide an extensive linguistic analysis to highlight the differences in language use between active citizens and misinformation posters. We also provide a qualitative analysis of the limitations of our best models in predicting accurately whether a user is an active citizen or a misinformation poster.

2 RELATED WORK

2.1 Misinformation: Definition and Types

Misinformation in social media can be generally defined as any false or incorrect information (e.g., fabricated news, rumors, etc.) that is published and propagated by end users [72]. Particularly, unverified posts in social media (i.e., rumors) are defined as any item of circulated information whose veracity is yet to be verified at the time of posting [76].

2.2 Misinformation Detection

Previous work on computational misinformation detection has focused on predicting the credibility or bias of news articles [4, 45, 48] and news sources [2, 5]. To prevent wide spread of misinformation, propagation-based detection methods are employed to enable early misinformation detection in social media [61, 73, 75]. In addition to using textual information, previous work on automated fact-checking also jointly use images and user profile information extracted from metadata associated with unreliable posts [26, 66].

Common automated fact-checking frameworks rely on external knowledge to determine the credibility of an unverified post, and they usually include one or more information retrieval models [18, 38]. Pre-trained language models (e.g., BERT [12]) have recently been applied for fact-checking without using any external knowledge [22, 27, 69] since they encapsulate factual knowledge from the massive amount of data used for pre-training, e.g., the English Wikipedia and Books Corpus [12].

These misinformation detection tasks mentioned above are usually performed on existing datasets, e.g., Liar [68] and FEVER [60] that typically contain claims associated with a label denoting if it is factual or not. These datasets do not usually include information on the user made the claim. Based on the publicly accessible Weibo Rumor Reporting Platform, Liu et al. [30] developed a Weibo rumor dataset with 7,055 misinformation posters and 4,559 active citizens, however, many users no longer exist as these rumor cases were collected between 2011 and 2013. Similarly, Song et al. [55] collected 3,387 rumor cases with their corresponding original publishers and 2,572,047 users who repost these fact-checked rumors.

2.3 User Behavior Analysis Related to Misinformation

Previous work in sociology and psychology have mostly used traditional survey-based methods to explore the personality traits [42, 58] and behavior [3, 59] of misinformation posters. A US-based survey shows that consumers of reliable mainstream news media are more likely to use fact-checking websites for checking the factuality of news claims [49]. Besides that, social media users are more inclined to trust debunked information that was shared by their network of friends rather than strangers [33].

Existing work on using computational approaches to misinformation analysis has analyzed the difference of users’ reactions (e.g., reply or retweet) to unreliable news sources and mainstream media as well as their characteristics (e.g., user demographic information) [14, 15]. To detect malicious accounts on social media, Addawood et al. [1] and Luceri et al. [31] have focused on identifying political trolls that diffuse misinformation and politically biased information during the US 2016 democratic election. Mu and Aletras [35] and Rangel et al. [47] focus on identifying Twitter users who diffuse unreliable news stories either on post level or news media level.

Vo and Lee [64] uncover the positive impact of misinformation active citizens on preventing the spread of false news. They found that around 7% of the original tweets (among 64k tweets) are irretrievable within five months of being debunked due to the suspension of the Twitter account and the deletion of tweets. This suggests that developing downstream tools (e.g., automatic generation of personalized fact-checking tweets [65, 66]) can encourage misinformation active citizens to actively prevent the spread of misinformation and help social media platforms to suspend malicious users. Moreover, active citizens who are active in sharing fact-checking information are found to use less informal language including swear words and are more likely to engage in debunking reliable posts about politics and fauxtography, i.e., photo edited images with misleading content [63]. Giachanou et al. [13] explore the impact of using linguistic features and user personality traits on identifying fake news posters and checkers based on 2,357 Twitter users.

Our work, on the other hand, is the first attempt to model active citizens who refute misinformation across different social media platforms and languages using our newly developed Weibo dataset and a substantially larger Twitter dataset than the one used by Giachanou et al. [13] which has not been employed yet for this task.

3 TASK AND DATA

3.1 Task Description

Following Giachanou et al. [13], we frame a binary classification task aiming to distinguish between users that tend to diffuse misinformation (i.e., misinformation posters) and users who actively tend to refute such unreliable posts (i.e., active citizens) using language information. Note that one could also use a user’s social network information for modeling the predictive task but this is out of the paper’s scope because we are interested in analyzing differences in language use between the misinformation posters and active citizens across different social media platforms. Given a
set of social media users, our task is to train a supervised classifier that can learn relations between users’ linguistic patterns (i.e., the collection of users’ original posts) and the corresponding class (i.e., misinformation posters or active citizens).

3.2 Weibo Data

In 2012, Weibo developed an official community management center to receive reports from end users for all kinds of malicious posts including misinformation, hate speech and content plagiarism. To combat misinformation, Weibo provides a fact-checking platform for its users to report any suspicious misinformation posts which are then subsequently fact-checked officially by the platform. These Weibo posts are eventually labeled as true or false. Alternatively, a post may also remain unverified until it has been fact-checked. In case that a post has been deemed to be labeled as false, it is also accompanied with debunking information refuting the claim. Figure 1 shows an example including the original publisher (e.g., misinformation poster), active citizen and fact-checking information on Weibo.

Collecting misinformation posters and active citizens. For the purpose of our experiments, we collect 38,712 debunked cases (between 2012 and 2020) from the official Weibo Community Management Center following a similar data collection approach as previous work [32, 71]. We keep only those posts that have been judged as false and then collect the corresponding poster (i.e., the original user that has published the post) and up to 20 recent active citizens (i.e., users that have officially reported that the post contains misinformation). Note that the official Weibo platform only allows access to the earliest 20 active citizens, even though some suspicious posts have been reported and refuted by more than 20 users. However, we notice that only in 709 cases there are more than 20 active citizens (i.e., less than 2% of all debunked posts). Given that some user accounts may have been suspended or become private, we remove those from the data.

Note that there is a difference in the definition of active citizens in Weibo and Twitter datasets. In Weibo, all active citizens are those who report misinformation to the Weibo Official Fact-checking Platform. In Twitter, active citizens are defined as ones who cite fact-checking URLs to refute misinformation. For consistency, we label all of these users as active citizens since they both actively try to refute misinformation. Weibo active citizens are not required to provide evidence or fact-checking ULRs but they are free to report a post on a suspicion that it contains misinformation.

Collecting User Posts. We use the Weibo API to collect up to 2,000 posts for each user since the median number of user posts are 968 and 855 for the two user categories (i.e., poster and debunker) respectively. We only consider users with more than 30 original posts and filter out all users who have both spread and debunk misinformation posts. After removing duplicate users, the final dataset contains 22,632 distinct posters and 25,702 distinct active citizens respectively.

| #Users | Poster AC | Poster AC |
|--------|-----------|-----------|
| Weibo  | 22,632    | 15,696    |
| Twitter| 17,293    | 2,824     |

| #Posts | Min | Max | Mean | Total |
|--------|-----|-----|------|-------|
| Weibo  | 31  | 2,000 | 596  | 13.5M |
| Twitter| 31  | 3,200 | 2,932| 46.0M |

| #Tokens/User | Min | Max | Mean | Median |
|--------------|-----|-----|------|--------|
| Weibo        | 127 | 104,947 | 13,643 | 4705 |
| Twitter      | 126 | 104,801 | 10,127 | 3,730 |

Table 1: Data Statistics.
3.3 Twitter Data

Collecting misinformation posters and active citizens. To label Twitter users as misinformation posters or active citizens, we use a publicly available dataset with totally 73,203 users provided by Vo and Lee [64].

Vo and Lee [64] first use the Hoaxy System [53] to collect fact-checking tweets (FC-tweets) that contain links to relevant fact-checking information from PolitiFact and Snopes. These FC-tweets contain users who post URLs from fact-checking websites as credible evidence to refute misinformation posts in public conversations on Twitter (i.e., active citizens). They also contain the original users whose posts are debunked (i.e., misinformation posters). Figure 2 shows an example that contains the original post, fact-checking tweets and the corresponding debunking information from Snopes. According to Vo and Lee [64], this dataset only contains misinformation active citizens who post English tweets with corresponding URLs linking to evidence (e.g., news article) that refutes a false claim. During data exploration, we observe that some Twitter users refer the fact-checking URLs to support the personal claims of the original posters, i.e., the original message has been proven correct. Therefore, we only consider users who share fact-checking URLs to refute tweets containing misinformation, i.e., those who are flagged as False by the corresponding fact-checking platform. In this way, we ensure that the selected active citizens have a clear intention to refute misinformation.

Collecting User Posts. For each Twitter user, we use the Twitter Public API8 to collect up to 3,200 tweets due to limits excluding any retweets. Moreover, we filter out users with less than 30 original tweets, users that may appear in both groups and keep users with a majority of English tweets (e.g., tweets that are labeled as ‘en’ or ‘en-gb’ by Twitter). As in the Weibo dataset, we also remove all users that both spread and debunk misinformation since we currently focus on the binary setting as in Giachanou et al. [13] since we found that less than 10% of all users fall into this category (i.e., both spread and debunk misinformation) in the two datasets. This process yielded 15,696 posters and 17,293 active citizens respectively. This is approximately 100 and 15 times larger than the datasets used in prior work [13, 47].

3.4 Data Statistics and Topical Coverage

Table 1 shows the descriptive statistics of the data including the number of tweets and tokens obtained from Weibo and Twitter. Both datasets cover a broader range of topics rather than a narrow subset of political misinformation. The Twitter dataset provided by Vo and Lee [64] is developed based on two popular fact-checking platforms (i.e., Snopes and PolitiFact) and covers more topics (e.g., medical and business) other than politics. However, we also notice that more than 50% of cases are related to politics given that one of the fact-checking platform (i.e., PolitiFact) is totally political oriented. As for the Weibo dataset, we collect all available cases of misinformation from the Weibo fact-checking platform from 2012 to 2020. According to Liu et al. [30], more than 90% of debunked Weibo misinformation are related to politics, economics, pseudo-science and social life.

3.5 Text Pre-processing

Weibo Posts. We pre-process the Weibo raw posts by converting all traditional Chinese words to simplified Chinese and then tokenizing using JIEBA, a Chinese text processing toolkit.10 We keep all non-Chinese words since we notice some common English words (e.g., python, hello, and world) are including in the training corpus of both Chinese and English transformer models.

Tweets. For the Twitter data, we follow a similar pre-processing pipeline11 as in Nguyen et al. [37]. In brief, we pre-process the tweets by first lowercasing and then tokenizing using the TweetTokenizer from NLTK toolkit [7]. Besides, we further normalize each Tweet by replacing each emoji,12 URL and @-mention with special tokens, i.e., single word token, @USER and HTTPURL respectively.

4 PREDICTIVE MODELS

4.1 Baseline Models

Logistic Regression. We apply logistic regression with L2 regularization penalty using Bag-of-Words (BOW) to represent each user as a TF-IDF weighted vector over a 10,000 sized vocabulary. We only keep n-grams appearing in more than 5 times and no more than 40% of the total users. We also represent each user over a distribution of manually created lexical categories represented by lists of words provided by the Linguistic Inquiry and Word Count (LIWC) 2015 dictionary [40]. LIWC has been extensively used in psycho-linguistic studies.

BiLSTM-ATT. Furthermore, we train a Bidirectional Long Short Term Memory network [19] with self-attention (BiLSTM-ATT) from scratch. The BiLSTM-ATT takes as input the users’ historical posts, maps their words to pre-trained word embeddings and subsequently passes them through a bidirectional LSTM layer. A user embedding is computed as the sum of the resulting context-aware embeddings weighted by the self-attention scores. The user embedding is then passed to the linear prediction layer with sigmoid activation.

4.2 English Transformers

BERT. Bidirectional Encoder Representations from Transformers [12] is a masked language model using a Transformer Network [62] pre-trained on the BooksCorpus and English Wikipedia.

RoBERTa. The Robustly Optimized BERT Pretraining Approach (RoBERTa) [29] is a BERT-style language model trained with fine-tuned hyper-parameters, larger batch size, and longer sequence compared to the original BERT. RoBERTa is trained on a combination of the original corpus used to train BERT and extra texts including English new articles and web content [29].

Longformer. The Long-Document Transformer (Longformer) [6] is pretrained using the original RoBERTa checkpoint [29] with a sliding window attention pattern (same window size of 512 as RoBERTa) and extra positional embeddings to support a maximum

---

8https://developer.twitter.com/en/docs
9We leave this multi-label classification task for future work
10https://github.com/fxsjy/jieba
11https://github.com/VinAIResearch/BERTweet
12We use the emoji Python package https://pypi.org/project/emoji/
length of 4.096 (from 512). Longformer can handle a longer text sequences and achieves state-of-the-art performance on long document下游NLP tasks [6].

4.3 Chinese Transformers

CBERT. For our Weibo prediction task, we first employ a Chinese BERT (CBERT) [11] model pretrained using a whole word masking strategy. CBERT is trained from the existing checkpoint of the Bert-Base-Chinese\(^{13}\) model, which has the same structure (e.g., layers and parameters) as the original BERT.

ERNIE. Enhanced Representation through Knowledge Integration (ERNIE) [57] is designed to learn language representations using knowledge masking strategies, i.e., entity-level masking and phrase-level masking. ERNIE is trained on both formal (e.g., Baidu Baike, a platform similar to Wikipedia and Chinese news articles) and informal (e.g., posts from Tieba, an open discussion forum similar to Reddit) Chinese corpora.

4.4 Handling Long Text

Transformer-based models cannot handle long sequences in a single standard GPU card due to the large memory requirements. To deal with this issue in our datasets, we experiment with truncated and hierarchical methods for all transformer-based models.

Truncated Transformers. Following similar work on modeling long texts by Sun et al. [56], we first employ a simple truncation method that cuts off the input to the maximum length supported by BERT and Longformer (e.g., 512 and 4,096 tokens). Following the same strategy as in Devlin et al. [12], we fine-tune transformer-based models by adding a linear prediction layer on the model special classification token, e.g., [CLS] of BERT and <s> of Longformer respectively.

Hierarchical Transformers. Given that the majority of users’ concatenated posts contain more than 512 tokens, we also use a hierarchical transformer structure [36, 39] (see Figure 3) for our long document classification task. We first split the input sequence (i.e., the collection of users’ original posts) into N = L / 510 chunks\(^{14}\) of a fixed length e.g., 512 including task special tokens (e.g., [CLS] tokens for BERT) and 4096 tokens for Longformer. For each of these word chunks, we obtain the representation of the [CLS] token from the fine-tuned BERT on our dataset. We then stack these segment-level representations into a sequence, which serves as input to a LSTM layer with a self-attention mechanism to learn a user-level representation. Finally, we add two fully connected layers with ReLU and sigmoid activations respectively on top of LSTM layer as in Pappagari et al. [39].

Following Sun et al. [56], we also test two simple hierarchical methods by directly using max pooling and mean pooling to stack the [CLS] embeddings of all the chunks of each user into a document-level representation.

5 EXPERIMENTAL SETUP

5.1 Hyper-parameters

For both Twitter and Weibo datasets, we train the models on the training set (70%) and tune the hyper-parameters on the validation set (10%). We tune the regularization parameter \(\alpha \in \{1e^{-1}, 1e^{-2}, 1e^{-3}, 1e^{-4}, 1e^{-5}\}\) of the Logistic Regression, setting \(\alpha = 1e^{-4}\). For BiLSTM-ATT, we use 200-dimensional GloVe embeddings [41] pre-trained on 2-billion tweets and 300-dimensional Chinese Word Vectors\(^{15}\) [28] pre-trained on Weibo data. We tune the LSTM hidden unit size \(\in \{50, 100, 150\}\) and dropout rate \(\in \{0.2, 0.5\}\) observing that 150 and 0.5 perform best respectively. For transformer-based models, we use BERT-Base-Uncased, RoBERTa-Base and Longformer-Base-4096 models fine-tuning them with learning rate \(lr \in \{5e^{-5}, 3e^{-5}, 2e^{-5}\}\) as recommended in Devlin et al. [12], setting \(lr = 2e^{-5}\). For the Chinese language models, we use Chinese-BERT-WWM-EXT and ERNIE-1.0 models fine-tuning them with learning rate \(lr \in \{5e^{-5}, 3e^{-5}, 2e^{-5}\}\) as in Cui et al. [11], setting \(lr = 2e^{-5}\). The maximum sequence length is set to 512 (including task special tokens, e.g., [CLS]) except the Longformer-Base-4096 which can handle a 4,096 input sequence length.

We use a batch size of 16 for all transformer-based models except the Longformer where we use batch size of 4. During training of the

Figure 3: Overview of the hierarchical transformer architecture used in our work. N = L / 510, where N denotes the number of chunks and L denotes the number of tokens. The Fusion Function denotes how we fuse the chunk-level information into the global representation, i.e., using Max Pooling, Mean Pooling and LSTM-Attention.

\(^{13}\)https://storage.googleapis.com/bert_models/2018_11_03/chinese_L-12_H-768_A-12.zip

\(^{14}\)\(N\) denotes the number of chunks and \(L\) the number of tokens.

\(^{15}\)https://github.com/Embedding/Chinese-Word-Vectors
neural models, we use early stopping based on the validation loss and then use the saved checkpoint to compute the model predictive performance on the test set.

5.2 Implementation Details
We perform all the experiments on a single NVIDIA V100 graphics card. We use the implementation of transformer-based models available from the HuggingFace library [70].

5.3 Evaluation Metrics
We run each model with the best hyper-parameter combination three times on the heldout set (20%) using different random seeds, and report the averaged macro precision, recall and F1 score (mean ± standard deviation).

6 RESULTS
6.1 Predictive Performance
Tables 2 and 3 show the results obtained by all models in the Weibo and Twitter datasets.

In Twitter, HierLongformer LSTM achieves the highest F1 score overall (80.2) surpassing all the baseline models as well as the simpler hierarchical architectures, e.g., using mean and max pooling. For each of the transformer-based model, we observe that the hierarchical transformer architectures (e.g., LSTM, max pooling and mean pooling) outperform the truncated models across all metrics. Their hierarchical structure allows them to exploit all the available textual information from each user that impacts performance. The Longformer model that supports longer input sequences achieves better predictive results than the other transformer models that support shorter input sequences (e.g., BERT and RoBERTa). This is similar to results obtained by Beltagy et al. [6], Gutierrez et al. [16] where the Longformer consistently outperforms other BERT-style models in long document classification tasks.

In Weibo, HierERNIE LSTM achieves the highest F1 score overall surpassing all other models. In addition, we observe two baseline models (LR-BOW and BiLSTM-ATT) achieve a slightly lower performance than the hierarchical transformers e.g., 82.7 and 82.9 F1-score respectively. This suggests that the relationship between users’ language use and labels can be learned more efficiently by using a simple classifier (e.g., LR) that has access to all users’ posts, compared to a more complex model that does not use all available information. We also observe that, in general, the use of different hierarchical methods (especially the LSTM takes into account the sequence order) improve the performance of truncated transformer models. This suggests that the order of the posts and their dependencies matter.

Lastly, we observe that the models with similar structure and characteristics trained on Weibo data are on average more accurate than the Twitter data (approximately 5%). This highlights that input language (i.e., Chinese vs. English) and its peculiarities play an important role in the performance of text classification models.

6.2 Model Explainability
For both datasets, we analyze the most important input tokens that contribute to the model prediction (i.e., HierERNIE LSTM in Weibo and HierLongformer LSTM in Twitter) by employing a widely used gradient-based explainability method i.e., the InputXGrad with L2 Norm Aggregation [25] that has been found to provide faithful explanations for transformer-based models in NLP tasks [9, 10].

The InputXGrad \( \nabla y \) ranks the input tokens by computing the derivative of the input with respect to the model predicted class and then multiplied by the input itself, where \( \nabla y = \frac{\partial \hat{y}}{\partial x} \). We then get the L2 normalized aggregation of the scores across the embedding dimensions similar to Chrysostomou and Aletras [9].

Twitter. In Twitter, the InputXGrad scores indicate that some hashtags and emojis (note that we have detokenized wordpieces when calculating importance scores) have a higher impact on model
predictions. For example, politics-related terms and hashtags (e.g., #POTUS) play an important role when the model predicts Twitter users as misinformation posters. This is similar to the result from Addawood et al. [1], showing that Twitter users using a higher number of political hashtags are more likely to be identified by the model as political trolls. On the other hand, some tokens related to daily activities (e.g., #yoga, #marchforscience, #vegetarian) and social issues (e.g., #blacklivematters) are more prevalent in misinformation active citizens.

Weibo. In Weibo, when the model predicts users as misinformation posters, some tokens that express emotions (e.g., surprise, unhappy and amazing) become the key factors. In contrast, model assigns importance to some popular buzzwords (e.g., hahahaha, xswl (i.e., LMAO in Chinese abbreviations) and celebrities (e.g., tfboys, uzi, and blackpink) when it predicts users as misinformation active citizens. These users who tend to debunk misinformation appear to be common users using Weibo for social interactions with friends.16

6.3 Error Analysis

We also perform an error analysis by inspecting cases of wrong predictions in both datasets. We first observe that Twitter active citizens who are wrongly classified as posters are more prevalent in posting about politicians (e.g., Obama, Clinton and POTUS) and some hashtags (e.g., #VOTEBIDEN, #BIDEN2020) related to the democratic party in the U.S.. These users are misclassified by the model possibly due to similar language use with those spreading misinformation. We also notice that Weibo misinformation posters who are misclassified as active citizens use cyber slang while are also more likely to express emotions e.g., Ahhh and 😂. We finally observe that a higher proportion of Weibo misinformation posters who are wrongly classified as active citizens are verified users (15%) (note that higher percentage of posters (21%) are verified users than active citizens (10%)).

Table 4: N-grams associated with Twitter misinformation posters and active citizens sorted by Pearson’s correlation (r) between the normalized frequency and the labels (p < .001).

| Posters       | n-grams  | Active Citizens | r   |
|---------------|----------|-----------------|-----|
| illegals      | 0.173    | slightly        | 0.154|
| msm (mainstream media) | 0.165    | empathy         | 0.154|
| U (regional indicator) | 0.158    | theories        | 0.144|
| S (regional indicator) | 0.154    | generally       | 0.141|
| soros         | 0.143    | equivalent      | 0.137|
| brennan       | 0.142    | necessarily     | 0.135|
| communist     | 0.140    | confusing       | 0.135|
| schumer       | 0.139    | fewer           | 0.131|
| leftist       | 0.130    | quotes          | 0.129|
| rino          | 0.128    | actively        | 0.129|

We translate all the Chinese N-grams into English.

Table 5: N-grams associated with Weibo misinformation posters and active citizens sorted by Pearson’s correlation (r) between the normalized frequency and the labels (p < .001).

| Posters | n-grams | Active Citizens | r   |
|---------|---------|-----------------|-----|
| cherish | 0.177   | WTF             | 0.256|
| understand | 0.172   | LMAO            | 0.249|
| present | 0.171   |                 | 0.239|
| this morning | 0.154   |                 | 0.232|
| because | 0.149   | rightmost       | 0.225|
| contact | 0.148   |                 | 0.222|
| rose    | 0.145   | awesome         | 0.218|
| strong  | 0.143   | Ahhh            | 0.214|
| creation | 0.139   | F*ck            | 0.202|

Figure 4: Words associated with misinformation posters (Red) and active citizens (Blue) on Twitter.

7 LINGUISTIC ANALYSIS

We further perform a linguistic analysis to uncover the differences in language use between users in the two categories, i.e. misinformation posters and active citizens. To that end, we employ univariate Pearson’s correlation test to characterize which linguistic features (i.e., BOW and LIWC17) are high correlated with each class following [52]. This approach has been widely used in similar NLP studies [21, 34, 46].

7.1 N-grams

Table 4 shows that Twitter users who diffuse misinformation are more prevalent in posting about politics (e.g., US, Soros and Brennan). This is similar to findings by Mu and Aletras [35], which

---

16 The letters U and S, which can be used as part of a regional indicator pair to create emoji flags for various countries.

17 We use the LIWC English [40] and Simplified Chinese [20] dictionaries.
showed that people who often retweeted news items from unreliable news sources (e.g., Infowars, Disclose.tv) are more likely to discuss politics. Moreover, active citizens on Twitter use more frequently adverbs (e.g., slightly, generally, and necessarily) and words that denote uncertainty (e.g., confusing). Table 5 shows that Weibo active citizens are more likely to use words related to self-disclosure, e.g., WTF, LMAO and awesome and net-speak words e.g., 😊 and right-most. These buzzwords are more popular among average Weibo users who share interesting posts with their friends or reply to something entertaining. Note that most of Weibo active citizens are not official accounts (i.e., unverified users) which rarely use these words. Similarly, Weibo active citizens also use emojis that express uncertainty, e.g., 😶, more frequently. We finally observe that Weibo misinformation posters use causation words (e.g., because). This is different from earlier studies that found deceivers to use a smaller number of causation words when telling false stories [17].

To better highlight the similarities between words associated with misinformation posters and active citizens, we also create two word clouds to display up to 100 N-grams features per user category in Twitter (see Figure 4) and Weibo (see Figure 5) datasets (i.e., the larger the font, the higher the Pearson correlation value).

We observe that the active citizens on both platforms like to use adverbs, for example, to express certainty (e.g., absolutely, equally, and particularly). Moreover, certain words are found to be strong indicators of truthfulness according to the interpersonal deception theory [1, 8]. In addition, active citizens also use words (e.g., disinformation, misleading, parody, and satire) which are partly used in fact-checking tweets to debunk suspicious posts on Twitter [63]. Compared to Weibo, Twitter misinformation posters discuss more global political events (i.e., politicians and parties) since Twitter is an international social media platform, while Weibo is used primarily by Chinese speakers.

7.2 LIWC

Tables 6 and 7 show the ten most correlated LIWC categories with each user class in Weibo and Twitter datasets respectively. We observe that users who belong to the misinformation poster class in both social media platforms are more prevalent in posting topics about Biological Processes (e.g., female, sexual and health) and Core Drives and Needs (e.g., Power, Drives, Affiliation and Achievement). Users who refute misinformation on social network post topics related to Cognitive Processes (e.g., Cogproc), e.g., Tentativeness, Differentiation, and Insight. On the other hand, Weibo active citizens use more frequently words belonging to LIWC categories such as informal and nonfluent (nonfluent) that are similar to their correlated N-grams (see Table 5).

8 CONCLUSION

In this paper, we have presented an extensive study on identifying and characterizing misinformation posters and active citizens across two different social media platforms (i.e., Twitter and Weibo) and languages (i.e. Chinese and English) for the first time. We developed a new Weibo dataset with users labeled into the two categories.
and repurposed an existing Twitter dataset for the task. Our hierarchical transformer model performs best, achieving up to 80.2 and 85.1 macro F1 score on Twitter and Weibo datasets respectively. Finally, we perform a linguistic feature analysis unveiling the major differences in language use between the two groups of users across platforms. In the future, we plan to explore cross-lingual settings for the task as well as including information from different modalities such as images [50, 51].

ETHICS CONSIDERATIONS
Our work has received ethical approval from the Ethics Committee of our department (Reference Number 025470) and complies with the Weibo and Twitter data policies for research.

To ensure the anonymity of the data, we only share the user’s ID, rather than the username that appears on the platform. We do not share the data for non-research purposes.

ACKNOWLEDGMENTS
We would like to thank Danae Sánchez Villegas, Mali Jin, George Chrysostomou, Xutan Peng and all the anonymous reviewers for their valuable feedback. Pu Niu is the corresponding author and supported by China Postdoctoral Science Foundation (No. 2021M701371).

REFERENCES
[1] Aseel Addawood, Adam Badawy, Kristina Lerman, and Emilio Ferrara. 2019. Linguistic cues to deception: Identifying political trolls on social media. In AAAI-ICWSM, Vol. 13. 15–25.

[2] Ahmet Aker, Kevin Vincentius, and Kalina Bontcheva. 2019. Credibility and Transparency of News Sources: Data Collection and Feature Analysis. In NewRevSIGIR. 15–20.

[3] Sacha Altay, Anne-Sophie Haquin, and Hugo Mercier. 2019. Why do so few people share fake news? It hurts their reputation. new media & society (2019), 1–15. 146448280968895.

[4] Ramy Baly, Giovanni Da San Martino, James Glass, and Preslav Nakov. 2020. We Can Detect Your Bias: Predicting the Political Ideology of News Articles. In EMNLP. 4982–4991.

[5] Ramy Baly, Georgi Karadzhov, Dimitar Alexandrov, James Glass, and Preslav Nakov. 2018. Predicting Factuality of Reporting and Bias of News Sources. In EMNLP. 3528–3539.

[6] Iz Belagay, Matthew E Peters, and Arman Cohan. 2020. Longformer: The long-document transformer. arXiv preprint arXiv:2004.05150 (2020).

[7] Steven Bird, Ewan Klein, and Edward Loper. 2009. Natural language processing with Python: analyzing text with the natural language toolkit. * O’Reilly Media, Inc..

[8] David B Buller and Jadee K Burgoon. 1996. Interpersonal deception theory. Communication theory 6, 3 (1996), 203–242.

[9] George Chrysostomou and Nikolaos Aletras. 2021. Improving the Faithfulness of Attention-based Explanations with Task-specific Information for Text Classification. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers). Association for Computational Linguistics, Online, 477–488. https://doi.org/10.18653/v1/2021.acl-long.40

[10] George Chrysostomou and Nikolaos Aletras. 2022. Flexible Instance-Specific Rationalization of NLP Models. In AAAI.

[11] Yiming Cui, Wansiang Che, Ting Liu, Bing Qin, Ziqing Yang, Shijin Wang, and Ziqing Yang. 2019. Document Classification for COVID-19 Literature. In EMNLP Findings 3715–3722.

[12] Jeffrey T Hancock, Lauren E Curry, Saurabh Goorha, and Michael Woodworth. 2007. On lying and being lied to: A linguistic analysis of deception in computer-mediated communication. Discourse Processes 45, 1 (2007), 1–23.

[13] Andreas Hanselowski, Hao Zhang, Zile Li, Danil Sorokin, Benjamin Schiller, Claudia Schulz, and Iryna Gurevych. 2018. UKP-Athena: Multi-Sentence Textual Entailment for Claim Verification. In 1st FEVER Workshop. 103–108.

[14] Sepp Hochreiter and Jürgen Schmidhuber. 1997. Long short-term memory. Neural computation 9, 8 (1997), 1735–1780.

[15] Mayank Jobanputra. 2019. Unsupervised Question Answering for Fact-Checking. EMNLP (2019), 52.

[16] Yiming Cui, Wanxiang Che, Ting Liu, Bing Qin, Ziqing Yang, Shijin Wang, and Ziqing Yang. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In NACL. 4171–4186.

[17] Anastasia Giachanou, Esteban A Rissola, Bilal Ghanem, Fabio Crestani, and Paolo Rosso. 2020. The role of personality and linguistic patterns in discriminating between fake news spreaders and fact checkers. In NLDB Springer, 181–192.

[18] Maria Gレンski, Tim Weninger, and Svitlana Volkova. 2018. Identifying and Understanding User Reactions to Deceptive and Trusted Social News Sources. In ACL. 176–181.

[19] Maria Gレンski, Tim Weninger, and Svitlana Volkova. 2018. Propagation from deceptive news sources who share, how much, how evenly, and how quickly?

[20] Bernal Jimenez Gutierrez, Jucheng Zeng, Dongdong Zhang, Ping Zhang, and Yu Su. 2020. Document Classification for COVID-19 Literature. In EMNLP Findings 3715–3722.

[21] Jeffrey T Hancock, Lauren E Curry, Saurabh Goorha, and Michael Woodworth. 2007. On lying and being lied to: A linguistic analysis of deception in computer-mediated communication. Discourse Processes 45, 1 (2007), 1–23.

[22] Andreas Hanselowski, Hao Zhang, Zile Li, Danil Sorokin, Benjamin Schiller, Claudia Schulz, and Iryna Gurevych. 2018. UKP-Athena: Multi-Sentence Textual Entailment for Claim Verification. In 1st FEVER Workshop. 103–108.

[23] Sepp Hochreiter and Jürgen Schmidhuber. 1997. Long short-term memory. Neural computation 9, 8 (1997), 1735–1780.

[24] Twin Karmakhar, Nikolaos Aletras, and Kalina Bontcheva. 2019. Journalist-in-the-Loop: Continuous Learning as a Service for Rumour Analysis. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP): System Demonstrations. Association for Computational Linguistics, Hong Kong, China, 115–120. https://doi.org/10.18653/v1/D19-3020

[25] Piet-Jan Kindermans, Kristof Schi¨att, Klaus-Robert M¨uller, and Sven D¨ahne. 2016. Investigating the influence of noise and distractors on the interpretation of neural networks. arXiv preprint arXiv:1611.07270 (2016).

[26] Kyomin Lee, Brian Eoff, and James Caverlee. 2011. Seven months with the devils: A long-term study of content polluters on twitter. In ACL. 157–162.

[27] Nayeon Lee, Belinda Z Li, Sinong Wang, Wen-tau Yih, Hao Ma, and Madiand Khabsa. 2020. Language Models as Fact Checkers?. In Proceedings of the Third Workshop on Fact Extraction and VERification (FEVER). 36–41.

[28] Shen Li, Zhe Zhao, Rengan Hu, Wen Li, Tao Liu, and Xiaoyong Du. 2018. Analytical Reasoning on Chinese Morphological and Semantic Relations. In ACL. 138–143.

[29] Yinan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized bert pretraining approach. arXiv preprint arXiv:1907.02802 (2019).

[30] Zhiyuan Liu, Le Zhang, CunChao TU, and MaoSung SUN. 2015. Statistical and semantic analysis of rumors in chinese social media. Scientia Sinica Informations 45, 12 (2015), 1536–1546.

[31] Luca Luceri, Silvia Giordano, and Emilio Ferrara. 2020. Detecting troll behavior via inverse reinforcement learning: A case study of Russian trolls in the 2016 US election. In AAAI-ICWSM, Vol. 14. 417–427.

[32] Ting Ma, Wei Gao, Prasenjit Mitra, Sejeong Kwon, Bernard J Jansen, Kam-Fai Wong, and Meeyoung Cha. 2016. Detecting rumors from microblogs with recurrent neural networks. In IJCAI-16. 3811–3824.

[33] Antonis Maronikolakis, Danae Sánchez Villegas, Daniel Preotiuc-Pietro, and Nikolaos Aletras. 2020. Analyzing Political Parody in Social Media. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics. Association for Computational Linguistics, Online. https://doi.org/10.18653/v1/2020.acl-main.403

[34] Yida Mu and Nikolaos Aletras. 2020. Identifying Twitter users who repost unreliable news sources with linguistic information. PeerJ Computer Science 6 (2020), e325.

[35] Andrzej Mulyar, Elliot Schumacher, Masoud Roubizadeh, and Mark Dreude. 2019. Phenotyping of clinical notes with improved document classification models using contextualized neural language models. arXiv preprint arXiv:1910.13664 (2019).

[36] Nat Quoc Nguyen, Thanh Vu, and Anh Tuan Nguyen. 2020. BERTweet: A pretrained language model for English Tweets. In EMNLP. 9–14.

[37] Yixin Nie, Haonan Chen, and Mohit Bansal. 2019. Combining fact extraction and verification with neural semantic matching networks. In AAAI, Vol. 33. 6559–6566.

[38] Rajagandha Pappagari, Piotr Zelasko, Jesús Villalba, Yishay Carmiel, and Najim Dehk. 2019. Hierarchical transformers for long document classification. In ASRU. IEEE, 838–844.
[40] James W Pennebaker, Martha E Francis, and Roger J Booth. 2001. Linguistic inquiry and word count: LIWC 2001. Mahwah: Lawrence Erlbaum Associates 71 (2001).

[41] Jeffrey Pennington, Richard Socher, and Christopher D Manning. 2014. GloVe: Global vectors for word representation. In EMNLP. 1532–1543.

[42] 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 (2018), 1865.

[43] Gordon Pennycook and David G Rand. 2019. Lazy, not biased: Susceptibility to partisan fake news is better explained by lack of reasoning than by motivated reasoning. Cognition 188 (2019), 39–50.

[44] Gordon Pennycook and David G Rand. 2020. Who falls for fake news? The roles of bullshit receptivity, overclaiming, familiarity, and analytic thinking. Journal of personality 88, 2 (2020), 185–200.

[45] Verónica Pérez-Rosas, Bennett Kleinberg, Alexandra Lefèvre, and Rada Mihalcea. 2018. Automatic Detection of Fake News. In COLING. 3391–3401.

[46] Daniel Preoțiuc-Pietro, Mihaela Gaman, and Nikolaos Aletras. 2019. Automatically Identifying Complaints in Social Media. In Proceedings of the 37th Annual Meeting of the Association for Computational Linguistics. Association for Computational Linguistics, Florence, Italy, 5098–5099. https://doi.org/10.18653/v1/P19-1495

[47] Francisco Rangel, Anastasia Giachanou, Bilad Ghanem, and Paolo Rosso. 2020. Overview of the 9th Author Profiling Task at PAN 2020: Factaying Fake News Spreaders on Twitter. In CLEF.

[48] Hannah Rashkin, Eunsol Choi, Jin Yeang, Svitlana Volkova, and Yejin Choi. 2017. Truth of varying shades: Analyzing language in fake news and political fact-checking. In EMNLP. 2931–2937.

[49] Craig T Robertson, Rachel R Mourão, and Esther Thorson. 2020. Who Uses Fact-checking? Explorations in Fact-checking URLs, Social Media, and fact-checking. In EMNLP. 1495–1506.

[50] Soroush Vosoughi, Deb Roy, and Sinan Aral. 2018. The spread of true and false news online. Science 359, 6380 (2018), 1146–1151.

[51] William Yang Wang. 2017. "Liar, Liar Pants on Fire": A New Benchmark Dataset for Fake News Detection. In ACL. 422–426.

[52] Evan Williams, Paul Rodrigues, and Valerie Novak. 2020. Accenture at CheckThat! 2020: If you say so: Post-hoc fact-checking of claims using transformer-based models. arXiv preprint arXiv:2009.02431 (2020).

[53] Thomas Wolf, Lysandre Déry, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Mat, Pierre Cistac, Tim Rault, Rémi Louf, Morgan Ponticoz, et al. 2019. Huggingface’s transformers: State-of-the-art natural language processing. arXiv preprint arXiv:1910.03771 (2019).

[54] Ke Wu, Song Yang, and Kenny Q Zhu. 2015. False rumors detection on sina weibo by propagation structures. In ICDE. IEEE, 651–662.

[55] James Thorne, Andreas Vlachos, Christos Christodouloupoulos, and Arpit Mittal. 2018. FEVER: A Large-scale Dataset for Fact Extraction and VERification. In NAACL. 809–819.

[56] Nguyen Vo and Kyumin Lee. 2020. Standing on the shoulders of guardians: Novel methodologies to combat fake news. In Disinformation, Misinformation, and Fake News in Social Media. Springer, 183–210.

[57] Nguyen Vo and Kyumin Lee. 2020. Where Are the Facts? Searching for Fact-checked Information to Alleviate the Spread of Fake News. arXiv preprint arXiv:2010.03159 (2020).

[58] Di You, Nguyen Vo, Kyumin Lee, and Qiang Liu. 2019. A State-independent and Time-evolving Network with Applications to Early Rumor Detection. In EMNLP. 9042–9051.

[59] Kantim Zhou, Chang Shu, Binyang Li, and Jey Han Lau. 2019. Early rumour detection. In NAACL. 1614–1623.

[60] Arkaitz Zubiaga, Ahmet Aker, Kalina Bontcheva, Maria Liakata, and Rob Procter. 2018. Detection and resolution of rumours in social media: A survey. Comput. Surveys 51, 2 (2018), 1–36.