



Data Article

Argumentation schemes, fallacies, and evidence in politicians' argumentative tweets—A coded dataset



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ABSTRACT

This coded database presents a corpus of argumentative tweets published by four politicians (Matteo Salvini, Donald Trump, Jair Bolsonaro, and Joe Biden) within 6 months from their taking office, which corresponds to the official end of their election campaign. The coding is based on a three-fold method of analysis based on the instruments of argumentation theory and pragmatics. First, the types of arguments are recognized and classified according to a systematic organization of the argumentation schemes developed in the literature. Second, arguments are evaluated considering the fallacies committed. Third, the uses and misuses of “emotive words” are assessed. Based on this theoretical framework, each tweet is thus attributed three categories of codes: 1) argument types (maximum two, corresponding to the most important ones); 2) fallacies (maximum two types of fallacies, plus a distinct indication of the lack of necessary evidence or false presupposition); and 3) emotive language (maximum three emotive words, plus the most important emotion expressed). A total of 2657 tweets are coded, providing a ground for comparative works and an instrument for training further coding of different corpora.

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Specifications Table

Subject	Humanities (General).
Specific subject area	Analysis and evaluation of arguments in messages posted by populist and non-populist political leaders on Twitter.
Type of data	Coded dataset.
How the data were acquired	The data were acquired from the institutional Twitter profiles of four political leaders: one (Joe Biden) representing the typical professional politician, and three (the Italian former minister for Internal Affairs, Matteo Salvini, the US president, Donald Trump, and the Brazilian president, Jair Messias Bolsonaro) commonly defined as “populists.” The tweets were retrieved automatically through the program Chorus [1], a software for the collection and analysis of tweets that visualizes the first 100 characters (out of 280) of each message, and then manually collected. The dataset includes the argumentative tweets of the politicians published during the first 180 days of their office, and more precisely: <ul style="list-style-type: none"> • Biden: from 3 November 2020 to 3 April 2021; • Trump: from 20 January 2017 to 19 July 2017; • Salvini: from 1 June 2018 to 28 November 2018; • Bolsonaro: from 1 January 2019 to 30 June 2019.
Data format	Fact-checked raw data.
Description of data collection	Annotated data based on a twofold annotation system. The data collected have been screened to identify only the argumentative tweets, excluding the following categories of messages: 1) tweets consisting in links to third parties’ articles or contents; 2) retweets or tweets substantially identical to others; 3) tweets solely expressing feelings, emotions, or evaluations, or only information, as not presumptively argumentative; 4) tweets that cannot mirror Toulmin’s argumentative structure, as not presumptively argumentative.
Data source location	The data have been coded by 3 independent annotators. Twitter: https://twitter.com/matteosalvinimi https://twitter.com/jairbolsonaro https://twitter.com/POTUS45 https://twitter.com/JoeBiden
Data accessibility	Considering that the Twitter accounts of Donald Trump were suspended, the tweets collected by the aforementioned source have been linked to the presently working database: https://www.presidency.ucsb.edu Repository name: Mendeley Data. Data identification number: DOI: 10.17632/bn37fhz96s.1 . Direct URL to data: https://data.mendeley.com/datasets/bn37fhz96s/1
Related research article	Macagno, Fabrizio. 2022. “Argumentation Profiles and the Manipulation of Common Ground. The Arguments of Populist Leaders on Twitter.” <i>Journal of Pragmatics</i> 191: 67–82. DOI: 10.1016/j.pragma.2022.01.022

Value of the Data

- The dataset of annotated arguments using argumentation schemes provides a gold standard corpus for training human annotators, and it can be adapted also for the purposes of machine learning in argument mining.
- The codification of the corpus using a systematic list of fallacies results in the first dataset of argument evaluation, which can be used for training students, coders, and machines in fallacy and argument identification and analysis.
- The codification of evidence use provides an original coded corpus for future works on argument structure and backing or student training on argument quality.
- The codification of the types of arguments and fallacies, if any, communicated in short written messages captures different rhetorical styles and manipulative strategies.
- The annotated data show different types of communicative relationships that political leaders developed with their audiences.

1. Data Description

The annotation of the types of argument and the fallacies characterizing an argumentative message is a growing need in several areas of research. First, in fields of logic and critical thinking, the analysis and the evaluation of arguments is taught at a theoretical level using textbook examples; however, the skills acquired by students or researchers on accurately selected or even invented cases are not sufficient for analyzing real messages. Moreover, the theoretical developments are normally top-down, namely they illustrate theoretical proposals using clear cases, and draw a clear and distinct line between a sound or strong argument and a fallacy. But this line is much more blurred and difficult to draw when we observe natural arguments and real-life corpora, characterized by ambiguity, distinct possible interpretations, and multiple implicit messages. Different criteria are needed for distinguishing one code from another – in our specific case one argument or one fallacy from another.

The philosophical domain is not the only field of study in which the instruments for analyzing arguments are needed. The linguistic areas devoted to discourse analysis and critical discourse analysis are increasingly focusing its efforts on the recognition and evaluation of persuasive and manipulative speech and the different aspects of arguments [2,3]. Such studies however, are mostly conducted qualitatively, often relying on complex theoretical frameworks drawn from philosophy of language or logic. The missing dialogue between the philosophical and the more applied linguistic field is mirrored by the lack of analytical tools such as codebooks for argument analysis or fallacy detection, and coded databases, which can be used for training coders and students.

Finally, argument and fallacy detection has drawn the attention of researchers in Artificial Intelligence and computational linguistics. One of the most ambitious projects in the field of Artificial Intelligence – and certainly the most promising in the area of argument and computation – is argument mining, namely the automatic identification and extraction not only of the arguments, but the types thereof. By detecting how a conclusion is defended, it is possible to both understand why people are holding a certain viewpoint, and provide the most popular or strongest reasons in support of a position [4]. This endeavor critically depends on the existence and accuracy of annotated corpora which can be used for training automatic classifiers.

The existence of shared, reliable, and relatively large, annotated datasets is thus essential for different disciplines and research interests. They can be a fundamental instrument for critical thinking teaching at different levels, allowing students to understand argumentative and manipulative strategies looking at real world examples. They would benefit annotators, who can train on a large amount of coded data. Finally, they can be adapted to automatic systems after being marked up and specifically adjusted to the annotation used in machine learning systems.

The availability of corpora depends on overcoming the same challenge underlying the use of argument analysis for quantitative studies, namely the lack of reliable coding systems grasping the distinctions between the types of arguments. The scarcity of annotated corpora [5] is aggravated by the use of different argument analysis methods, which range from simple annotation of argument elements (premise, conclusion) to the coding of types of argument specific to a certain discipline [4]. A further problem is the reliability of such corpora. The distinctions between the arguments are only rarely grounded on a theoretical background – the differences are empirically drawn based on observations or field-related concepts, but they are not theoretically justified. More importantly, very rarely do the few available annotated corpora include detailed information about the coding procedure and accurate reliability measures [6]¹.

The purpose of this annotated dataset is to provide a gold standard corpus for the detection and evaluation of arguments in political discourse [7–9]. The data consist of tweets published by four politicians, namely the Italian former minister for Internal Affairs, Matteo Salvini, the former US president, Donald Trump, the present Brazilian president, Jair Messias Bolsonaro, and the present US president, Joe Biden, using their institutional Twitter profiles. The choice of this platform is related to its twofold relationship with the news world [10], as it is used by journalists both for disseminating news to the public, and for acquiring information, which makes it an extremely powerful, but risky, political tool. The choice of the authors of the messages is based on two criteria. First, they represent the politicians who actively use Twitter as an instrument for defending specific positions and justifying their choices. Second, they represent two categories of leaders, the so-called “populists”² (Salvini, Trump, Bolsonaro) and the non-populist ones (Biden). The tweets of the four politicians have been collected for 180 days starting from the date on which they took office – providing a representative corpus of their official communications.

The database has been constructed automatically through the program Chorus [1], a software for the collection and analysis of tweets that originally visualized the first 100 characters (out of 280) of each message (later extended to 280 characters at the time this paper was written). Chorus allowed the retrieval of all the messages within the set timeframe; the first 100 characters were used then for manually identifying the full tweet, which is collected and reported in the database. Considering that the purpose of this database is providing a coded dataset of argumentative messages, only the textual content of the tweets has been reported without any alteration. The tweets collected have been screened to identify only the argumentative ones. The screening procedure was based on the following four exclusionary criteria:

1. Formal criterion 1. Exclusion of the tweets consisting in links to articles or contents authored by third parties as not advancing an argument.
2. Formal criterion 2. Exclusion of the retweets or tweets substantially identical to previous ones, as not aimed at providing an argument, but rather reinforcing or reminding.
3. Pragmatic criterion. Exclusion of the tweets solely expressing feelings, emotions, or evaluations, or only information, as not presumptively argumentative.
4. Structural criterion. Exclusion of the tweets that cannot mirror the basic argumentative structure (either complete or partial) outlined by Toulmin [11], as not presumptively argumentative.

¹ See for instance one of the most used corpora that integrates the annotation of arguments by types, which, however, fails to indicate any interrater agreement: http://araucaria.org.tech/doku.php#araucaria_argumentation_corpus (Last accessed on 31 July 2022).

² Rachman, G. (2018). Sex, violence and the rise of populism. *The Financial Times*, 1 October 2018 (retrieved from <https://www.ft.com/content/dfcfc632-c552-11e8-8670-c5353379f7c2> on 5 September 2020).

Further to the exclusionary criteria, the following inclusionary criterion has been used to assess the tweets not previously excluded:

5. Pragmatic-structural criterion. Inclusion of the tweets that: a) provide factual (verifiable) information (including also reported speech) or opinion to support a conclusion or backed by reasons; b) express conclusions as rhetorical questions.

The use of these five criteria led to an argumentative comparative corpus consisting of 2657 argumentative tweets (Fig. 1).

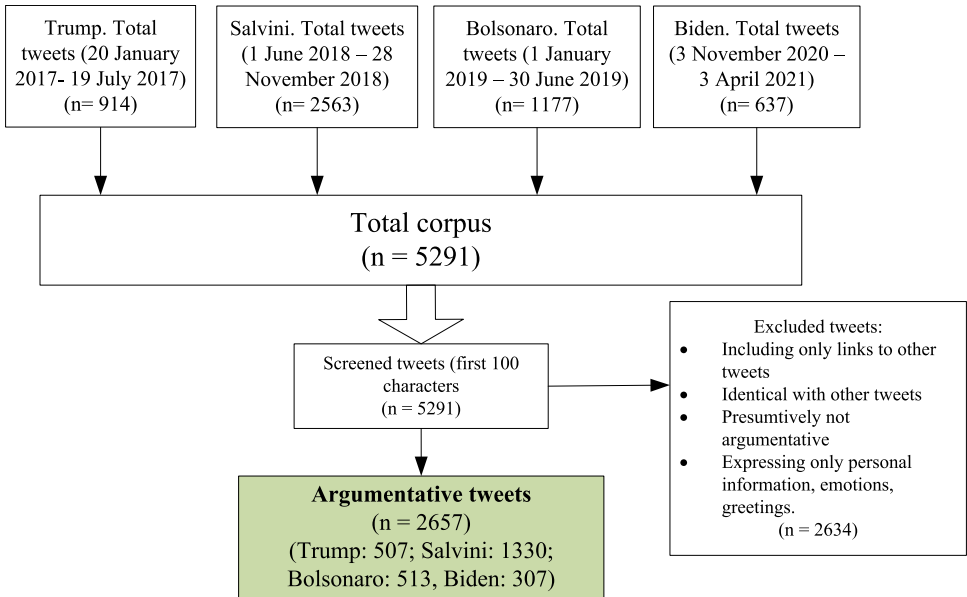


Fig. 1. Corpus construction.

As Fig. 1 shows, the argumentative tweets represent on average about 50% of the tweets. The distribution of the tweets by the four leaders reveals sharp differences: Salvini posted more than 14 tweets per day, more than the double of both Bolsonaro (6,5) and Trump (5), and almost four times more than Biden.

This dataset has been annotated following a specific procedure. First, the tweets have been read by the coders, using the multimedia information (links, images, videos, or comments) only for disambiguating the message. Each tweet has been associated with a unique ID and linked to its original source, namely the URL of the original post – or, in case of the tweets of Donald Trump (whose Twitter accounts have been suspended), the URL of the database page that collected the deleted messages (<https://www.presidency.ucsb.edu>). Second, when the message refers to verifiable information (data, facts, others' statements, etc.), such information has been checked considering reliable sources (newspapers articles; recordings of the original speech reported; statistics) to establish whether it was accurately reported. When there is clear evidence that the information reported in the tweet is controversial, a report is indicated in a devoted column ("Fact Check") together with the link to the source of the evidence, when available and when needed for verifying the accuracy of the information. The report does not indicate the falsity of the information conveyed explicitly or implicitly in the message; rather, it signals the

existence of evidence that contradicts or is incoherent with it, which makes the quote or the information potentially controversial. The fact-checked tweet appears as follows (Table 1):

Table 1

Fact-checked tweet.

ID	TWEET	FACTCHECK
TR19	Ungrateful TRAITOR Chelsea Manning, who should never have been released from prison, is now calling President Obama a weak leader. Terrible!	Manning's column suggested Mr Obama had "very few permanent accomplishments" because his attempts at compromise were met with "unparalleled resistance from his opponents, many of whom wanted him to fail". (https://www.theguardian.com/commentisfree/2017/jan/25/compromise-doesnt-work-political-opponents-chelsea-manning)

In contrast, when there is no available information disconfirming the accuracy of the information reported by the tweet, no notes are added.

The data are organized in 5 Microsoft Excel sheets. The first sheet reports the codes used for the annotation, while the remaining 4 sheet display the fact-checked annotated tweets of each speaker (one sheet per political leader). Each sheet consists of 14 columns. The first three columns report the tweet ID, the original post, and the fact-check report. The remaining 11 columns provide three types of annotation. The first code captures the type of argument that the tweet expresses, and more specifically the (at most) two most important arguments (columns "Argument 1" and "Argument 2"), either linked or chained (4th and 5th column). The second code captures the fallacies committed, if any (the 6th and 7th column), namely the classical types of manipulation. The 8th and the 9th column represent two additional criteria for determining the quality of an argument, namely the presence of unacceptable or unshared presuppositions (column "pp") and the absence of evidence required to make the argument acceptable (column "Evidence") (Table 2).

Table 2

Annotation appearance – argument types and quality.

ID	TWEET	FACTCHECK	Arg. 1	Arg. 2	FALLACIES	FALLACIES	pp	Evidence
TR19	Ungrateful TRAITOR Chelsea Manning, who should never have been released from prison, is now calling President Obama a weak leader. Terrible!	Manning's column suggested Mr Obama had "very few permanent accomplishments" ...	AH		SM	IQ	X	

The remaining 5 columns are descriptive. Here the annotators reported the emotive words used, if any, namely the terms that are used to trigger a value judgment, for a maximum number of 3 emotive words per tweet (10th, 11th, 12th column). This descriptor allows the identification of the frequency of specific emotive words in each speaker, which can be further analyzed. The emotive words can be represented in word clouds to outline the composition of each speaker's word choice (Figs. 2–5).



Fig. 2. Trump's frequency of emotive words.



Fig. 3. Biden's frequency of emotive words.



Fig. 4. Bolsonaro's frequency of emotive words.



Fig. 5. Salvini's frequency of emotive words.

The last descriptive dimension is the use of emotions, coded in the last two columns.

2. Design, Materials and Methods

The data have been coded using a twofold coding system, based on two distinct codebooks [7]. The first type of coding captures the types of argument, while the second the fallacies, if any, present in the argumentative messages. In addition to these two primary codes, the unacceptable presuppositions and the lack of necessary evidence were coded. These two additional codes are used for providing further elements for the evaluation of an argument. The presence of fallacies and unshared presuppositions are indicators of a manipulative effort, while the lack of evidence to be provided in support of a potentially controversial premise is a strong sign of arguments that are not presumptively acceptable. The relationship between these quality criteria is represented at Fig. 6.

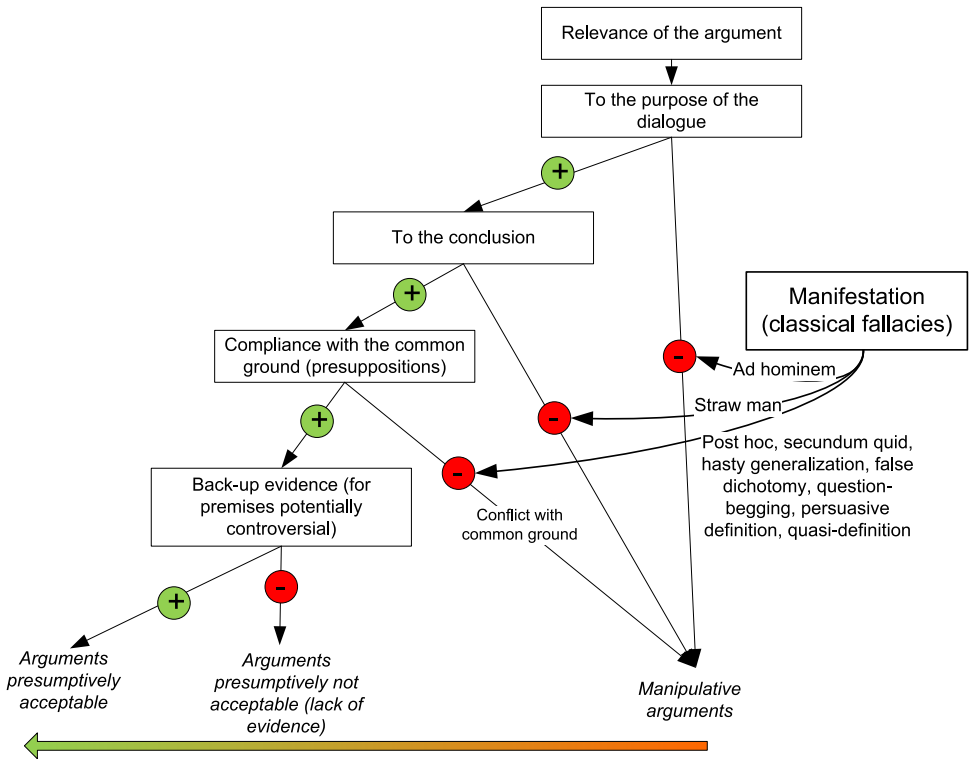


Fig. 6. Acceptability of arguments.

This figure represents the continuum between presumptively acceptable and presumptively unacceptable arguments used for manipulative purposes [8]. Arguments can be irrelevant to the type of dialogue in which the interlocutors are engaging. For example, in a dialogical setting in which a political authority is presumed to provide citizens with information about and reasons for political decisions, personal attacks twist the purpose of the whole interaction, as they presume that the target of the attack and the speaker are involved in a personal quarrel, or that the target is a source of authority that is in this way scrutinized and questioned. Some arguments are used to support a conclusion that is not the one under discussion in the dialogue – for example, a speaker can attack a viewpoint that is not the one defended by the interlocutor

or provide a reason in support of a claim that is only apparently similar to what the conversation is about. Moreover, a speaker can use an unshared premise without making it explicit, taking for granted that is commonly accepted. For example, when Trump claims that the “Fake News story of secret dinner with Putin is sick” (TR504 in the database), he is taking for granted that the story has been authored by newspapers that spread fake news, which is not commonly accepted and is indeed contrary to evidence. In addition to unaccepted presuppositions, evidence is an additional fundamental aspect of argument assessment. In a context of uncertainty, a potentially controversial premise or conclusion can be accepted if evidence is provided, as the burden of proof is on the speaker. For example, when a speaker is grounding his or her conclusion on generalizations unbacked by any evidence, she or he is failing to meet the burden of proof, and the conclusion cannot be presumptively accepted.

For these reasons, the codes “presupposition” and “evidence” were included as elements needed for justifying the evaluation of a message as fallacious or problematic. Two further descriptors are included in the annotated database, namely the detection of the emotive words and the emotions triggered. These elements capture an essential aspect of the rhetorical structure of a message, which consists in the arousal of specific emotions for strategic purposes.

2.1. Annotation of the types of argument

Argumentation schemes, and in particular the ones developed by Walton and colleagues [12] are one of the most used instruments for classifying the types of arguments. However, the literature lists and describes more than 60 schemes [12], which makes the reliability of the coding almost impossible to achieve. For this reason, based on several works aimed at simplifying the system of argumentation schemes [13,14], 13 basic schemes were selected, combining some schemes (such as position to know/expert opinion, and analogy/example) in macro categories in order to allow an easier detection. The codes are represented in the following Table 3.

Table 3
Coding scheme—argumentation schemes [7].

Argument category	Argument	Example
1. Practical arguments	1. Argument from consequences (AC)	a. <i>If the ban were announced with a one week notice, the “bad” would rush into our country during that week. A lot of bad “dudes” out there!</i>
	2. Argument from practical reasoning. (PR)	b. <i>For criminals, drug dealers, and murderers who bring war to our home, there is only one solution: EXPULSION.</i>
	3. Argument from commitment (CO)	c. <i>The crackdown on illegal criminals is merely the keeping of my campaign promise.</i>
2. Evaluative arguments	4. Argument from values (AV)	d. <i>Peaceful protests are a hallmark of our democracy. Even if I don’t always agree, I recognize the rights of people to express their views.</i>
	5. Victimization (VV)	e. <i>It is amazing how rude much of the media is to my very hard working representatives. Be nice, you will do much better!</i>
3. Source-based (external) arguments	6. Argument from expert opinion/position to know (PK)	f. <i>FoxNews from multiple sources: “There was electronic surveillance of Trump, and people close to Trump. This is unprecedented.” @FBI</i>
	7. Argument from popular opinion. (PO)	g. <i>Everyone acknowledges that the fundamentals of the Italian economy are good and do not correspond to the present spread.</i>
	8. Ad hominem argument. (AH)	h. <i>The failing @nytimes does major FAKE NEWS China story saying “Mr.Xi has not spoken to Mr. Trump since Nov.14.”</i>

(continued on next page)

Table 3 (continued)

Argument category	Argument	Example
4. Discovery arguments	9. Argument from cause to effect. (CE)	i. <i>If people do not work, they cannot invest in the FUTURE and cannot have CHILDREN</i>
	10. Argument from best explanation. (BEX)	j. <i>Watched protests yesterday but was under the impression that we just had an election! Why didn't these people vote?</i>
	11. Argument from sign (AS)	k. <i>Stock market hits new high with longest winning streak in decades. Great level of confidence and optimism - even before tax plan rollout!</i>
5. Other	12. Argument from analogy/example (AA)	l. <i>Thanks to Trump's tax cuts, the American economy started to grow again. Step by step, by introducing the flat tax also in Italy, the production, the work, the consumes, and our country will start to grow again.</i>
	13. Argument from Classification (CLASS)	m. <i>What we witnessed yesterday was not dissent – it was disorder. They weren't protestors – they were rioters, insurrectionists, and domestic terrorists.</i>

The choice of an argumentation over another in case of doubt is based on the complexity criteria:

- a. The argumentation scheme that describes more fully the argument prevails over the one that describes only one aspect, and
- b. If an argumentation scheme explains more aspects of the argument than another argumentation scheme, the more explanatory argumentation scheme should be chosen.

For example, an *ad hominem* involves an evaluation – a value judgment on the speaker. However, an *ad hominem* is not only an evaluation, as the latter is the ground for attacking the credibility of what has been said. Thus, in case the speaker undermines the credibility of what the interlocutor or a third party claimed through a personal attack (negative evaluation), the argument is not from values, but *ad hominem*.

This coding scheme was tested for reliability through interrater agreement. The coding of the sample size amounted to 20% of the argumentative tweets randomly selected within the corpus ($N = 530$). The agreement between coders was substantial (Krippendorff's Alpha (categorical) = .791; $\kappa = .791$ $p < .001$).

2.2. Evaluation of arguments

9 codes were used to capture the fallacies, combining a top-down approach, based on the dimensions of an argument, and with a bottom-up one, considering both the literature on the analysis of the quality of written arguments and pilot studies. These fallacies represent three distinct strategies: 1) manipulation of a viewpoint; 2) manipulation of the common ground; and 3) manipulation of word use. The codes are summarized and illustrated in Table 4, which illustrates them through examples from the corpus.

Table 4

Categories of manipulation and fallacies [7].

Manipulation strategy	Fallacy	Example
1. Topical irrelevance (attacking or using a viewpoint that is not the one advanced)	1. <i>Straw man</i> (a modification of the viewpoint or a claim of the interlocutor for attacking it more easily) (SM)	a. <i>Remember when the failing @nytimes apologized to its subscribers, right after the election, because their coverage was so wrong. Now worse!</i> ³
2. Presuppositions in conflict with the <i>common ground</i> 2.1. Facts	2. False dichotomy (contrary or alternative options or states of affairs presupposed as contradictory) (FD) 3. <i>Ignoring qualifications</i> (presupposing that the premise includes the qualifications necessary for drawing the conclusion) (IQ) 4. Question begging epithets (the use of a word or syntactical structures presupposes unproven or unaccepted judgments or states of affairs) (QB)	b. <i>Somebody with aptitude and conviction should buy the FAKE NEWS and failing @nytimes and either run it correctly or let it fold with dignity!</i> c. <i>After being forced to apologize for its bad and inaccurate coverage of me after winning the election, the FAKE NEWS @nytimes is still lost!</i> (The Times has not apologized for their coverage of Trump during the election, but did send an email to subscribers saying they underestimated the business mogul's chance of winning.) d. <i>Don't let the fake media tell you that I have changed my position.</i> (presupposing that there are fake media) e. <i>January 20th 2017, will be remembered as the day the people became the rulers of this nation again.</i> (presupposing that people were not rulers before 2017)
2.2. Specific warrants	5. <i>Post hoc ergo propter hoc</i> (a temporal or spatial coincidence or succession presupposed as a cause-effect relation) (PH) 6. Hasty generalization (from specific events to a universal generalization) (HG) 7. Slippery Slope (consequences unwarranted by the facts, too exaggerated) (SS)	f. <i>f. The weak illegal immigration policies of the Obama Admin. allowed bad MS 13 gangs to form in cities across U.S. We are removing them fast!</i> (Obama introduced immigration measures and MS 13 gangs developed in the US; the two things are only temporally related – not by cause-effect) g. <i>The Fake News media is officially out of control. They will do or say anything in order to get attention - never been a time like this!</i> h. <i>If the ban were announced with a one week notice, the "bad" would rush into our country during that week. A lot of bad "dudes" out there!</i>
2.3 Word meaning or connotation	8. Persuasive definition (implicit modification of the meaning of words) (PD) 9. Quasi-definition (takes for granted unshared or not commonly accepted inferences from the use of a word) (QD)	i. <i>If our healthcare plan is approved, you will see real healthcare and premiums will start tumbling down. ObamaCare is in a death spiral!</i> j. <i>How strange, in these latter months, these foreign "big journals" have become all experts in Italian politics. ("Big journals" – giornaloni in Italian – is associated with a negative connotation)</i> k. <i>The "democrats" daddy's boys occupy a building in Milan, shouting "Salvini is shit." But haven't they anything better to do?</i>

The choice of a fallacy over another in case of doubt is based on the complexity criteria:

- a. The fallacy that describes more fully the deceptive move prevails over the one that describes only one dimension, and
- b. If a fallacy explains more aspects of the deceptive move than another fallacy, the more explanatory fallacy should be chosen.

For example, a straw man can be based on ignoring qualifications. However, the straw man describes a manipulation (through ignoring qualifications) that is used to attack the interlocu-

tor. Thus, the straw man is more complex and more explanatory than the ignoring qualification (describes the whole fallacy in all its dimensions).

This coding system has been validated by interrater agreement on sample size amounting to 20% of the argumentative tweets randomly selected within the corpus ($N = 530$). The agreement between coders was substantial (Krippendorff's Alpha (categorical) = 0.776; $\kappa = .776$, $p < .001$).

2.3. Emotive words and the use of emotions

The descriptive codes of the database refer to the so-called emotive words, namely words used to trigger a specific value judgment, and the emotions potentially aroused. The identification of such words is based on two criteria: 1) their argumentative function, namely their role as premises for justifying an explicit or implicit value judgment, and 2) the lack of other reasons in support of such a value judgment. The codification of emotions is the result of the combination of all the previous codes and descriptions, which identify the possible argumentative uses of emotions (attacks; victimizations; values) and the potential triggers of emotions (emotive words).

Ethics Statements

This work involves data collected from social media platforms. According to Twitter's Terms of Service and Privacy Policies, by agreeing to two Twitters terms and service agreement, users consent to the public nature of the tweets and their use by third parties [15]. Pursuant to this latter agreement,⁴ "Most activity on Twitter is public, including your profile information, your display language, when you created your account, and your Tweets and certain information about your Tweets like the date, time, and application and version of Twitter you Tweeted from." The procedure for data collection has not been infringed, as tweets have been manually collected from Twitter (Chorus has been only used for identifying the tweets published in the given timeframe). Moreover, the academic level of the Twitter API has been requested and obtained (application no. 22192028), allowing the use of Twitter for research purposes. Pursuant to Twitter's Developer Agreement (entered by executing the license to use the Development Portal of Twitter API), the author is allowed to "modify Twitter Content only to format it for display on your Services" (at B.3)⁵. The User ID of the speakers has been identified both in the database (on a separate sheet) and in the present paper (the tweets of Donald Trump have been retrieved from @realDonaldTrump before his account being permanently suspended; these tweets can be found at the following repository: <https://www.presidency.ucsb.edu>). The content of the tweets has been modified only to adapt them to the excel format, eliminating elements (such as emoticons) that would result in different symbols in the excel format and hyperlinks.

CRediT Author Statement

The author confirms sole responsibility for the following: Conceptualization, Data curation, Methodology, and Writing.

³ Borchers, C. (2017). No, the New York Times did not apologize because its Trump coverage was 'so wrong'. *The Washington Post*, March 29, 2017 (retrieved from <https://www.washingtonpost.com/news/the-fix/wp/2017/03/29/no-the-new-york-times-did-not-apologize-because-its-trump-coverage-was-so-wrong/> on 4 September 2020).

⁴ Twitter Privacy Policy. Retrieved from <https://twitter.com/en/privacy> (last accessed on 26 October 2021).

⁵ Developer Agreement. Retrieved from <https://developer.twitter.com/en/developer-terms/agreement-and-policy> (last accessed on 26 October 2021).

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests.

Data Availability

Argumentative Tweets Analysis - Language of Populism (Original data) (Mendeley Data).

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