Semantic Networks: a definition

- WHAT — graphical representations of knowledge based on meaningful relationships of written text, structured as a network of labeled nodes cognitively related to one another
- WHY — GOAL: extract meanings
- HOW — semantic networks connect words to words/hashtags/phrases, based on their co-occurrence
- WHO — human and computerized methods, dealing with challenges such as co-reference resolution, synonym resolution, and ambiguity

How good are the retrieved docs?

Precision : “purity” Fraction of retrieved docs that are relevant to the user’s information need (reject irrelevant)

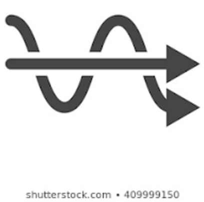
Recall : “completeness” Fraction of relevant docs in collection that are retrieved (select relevant)

CLEAN DATA

Pre-processing starts the text preparation into a more structured representation.

1) **Tokenization:** Tokenization is used to identify all words in a given text.
2) **Data Filtering:** People use a lot of casual language on twitter. To improve this and make words more similar to generic words, such sets of repeated letters are replaced by two occurrences.
haaaaappy -> haappy.

3) **Stop Word Removal**: Is used to eliminate that words that occurs frequently such as article, prepositions, conjunction and adverbs. These stop words depends on language of the text in questions. For example, words like the, and, before, while, and so on do not contribute to the sentiment.



4**) Stemming:** In information retrieval, stemming is the process of reducing a word to its root form.
walking, walker, walked ->walk

The process of “stemming” is removing these endings from words in a corpus. A “lemma” is a more linguistically informed version of a stem, such that “fight” is the lemma of “fought.”

Cleaning products

- Natural Language Toolkit (NLTK) in Python (Loper & Bird, 2002)
- Text Mining (tm) library in R (D. Meyer et al., 2008)

Common Tokenization Implementations in Python and R Programming Languages

	Description	Language/Library/function
Regular Expressions	Pattern matching algorithms that are fast and customizable.	R/tm/Regexp_Tokenizer[4]
CoreNLP Tokenizer	Rule-based, extensive support for many (human) languages.	Python/stanza[5]
Punctuation Tokenizers	Punctuation-sensitive, splits contractions	Python/nltk/word_tokenize[6]
Tokenizers for Social Media	Twitter and other media have specific conventions that need to be parsed by dedicated approaches	R/tokenizers/tokenize_tweets[7]
Model-specific tokenizers	Methods in NLP use tokenizers that automatically identify lemmas, contractions, and some parts of speech	Python/transformers/tokenizer[8]

4https://rdrr.io/rforge/tm/man/tokenizer.html

5https://github.com/stanfordnlp/stanza

6https://www.nltk.org/api/nltk.tokenize.html

7https://cran.r-project.org/web/packages/tokenizers/vignettes/introduction-to-tokenizers.html

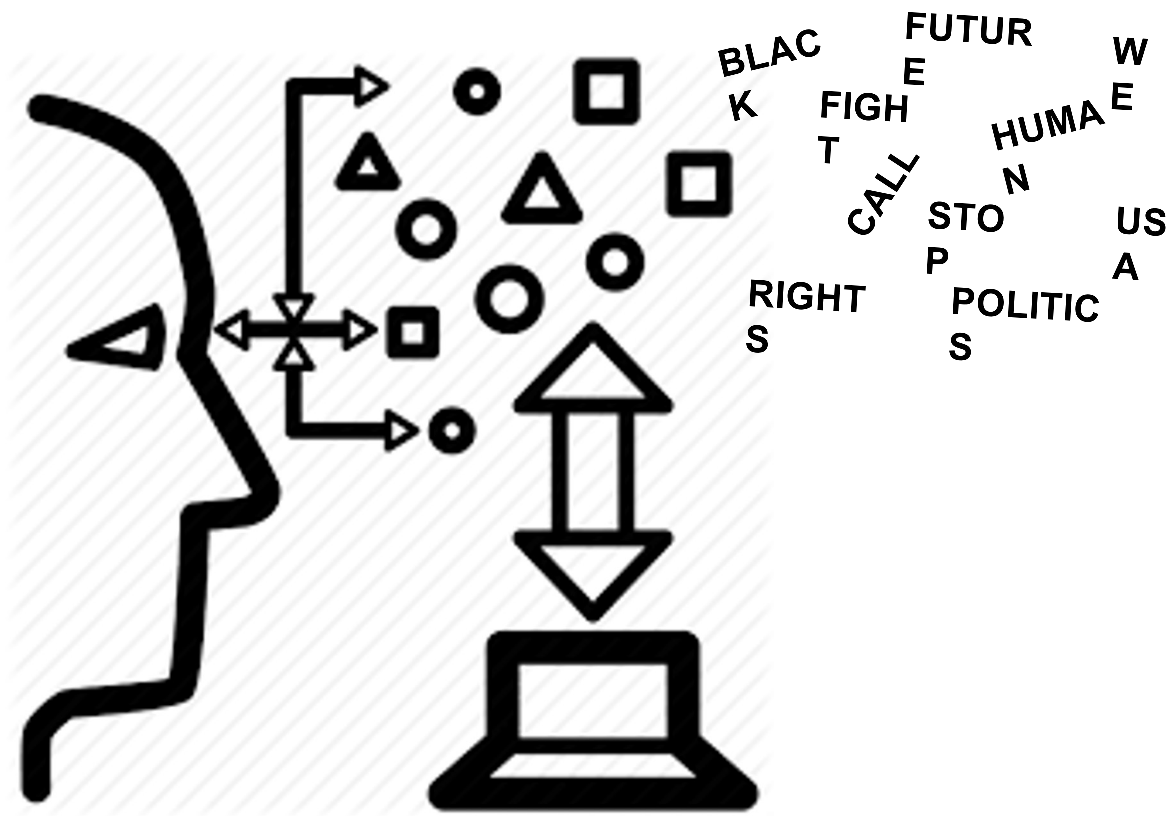
8https://github.com/huggingface/tokenizers

STEMMMING →

https://www.rdocumentation.org/packages/corpus/versions/0.10.1/topics/stem_snowball
https://www.kite.com/python/docs/nltk.SnowballStemmer
WordNet Lemmatizer: https://pythonprogramming.net/lemmatizing-nltk-tutorial/

PROCESS DATA

Dealing with textual data: from text to numbers

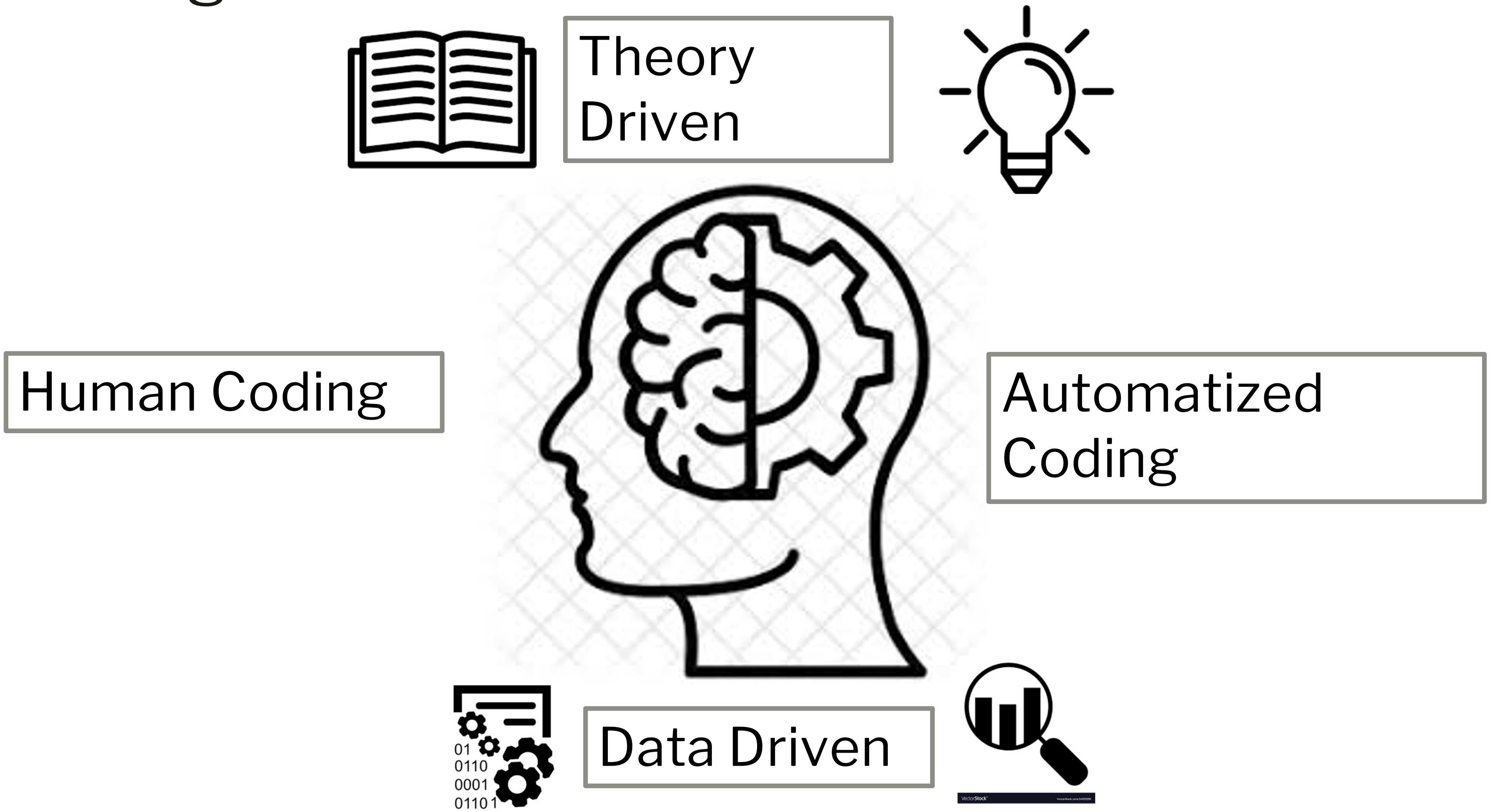


Words or Hashtags

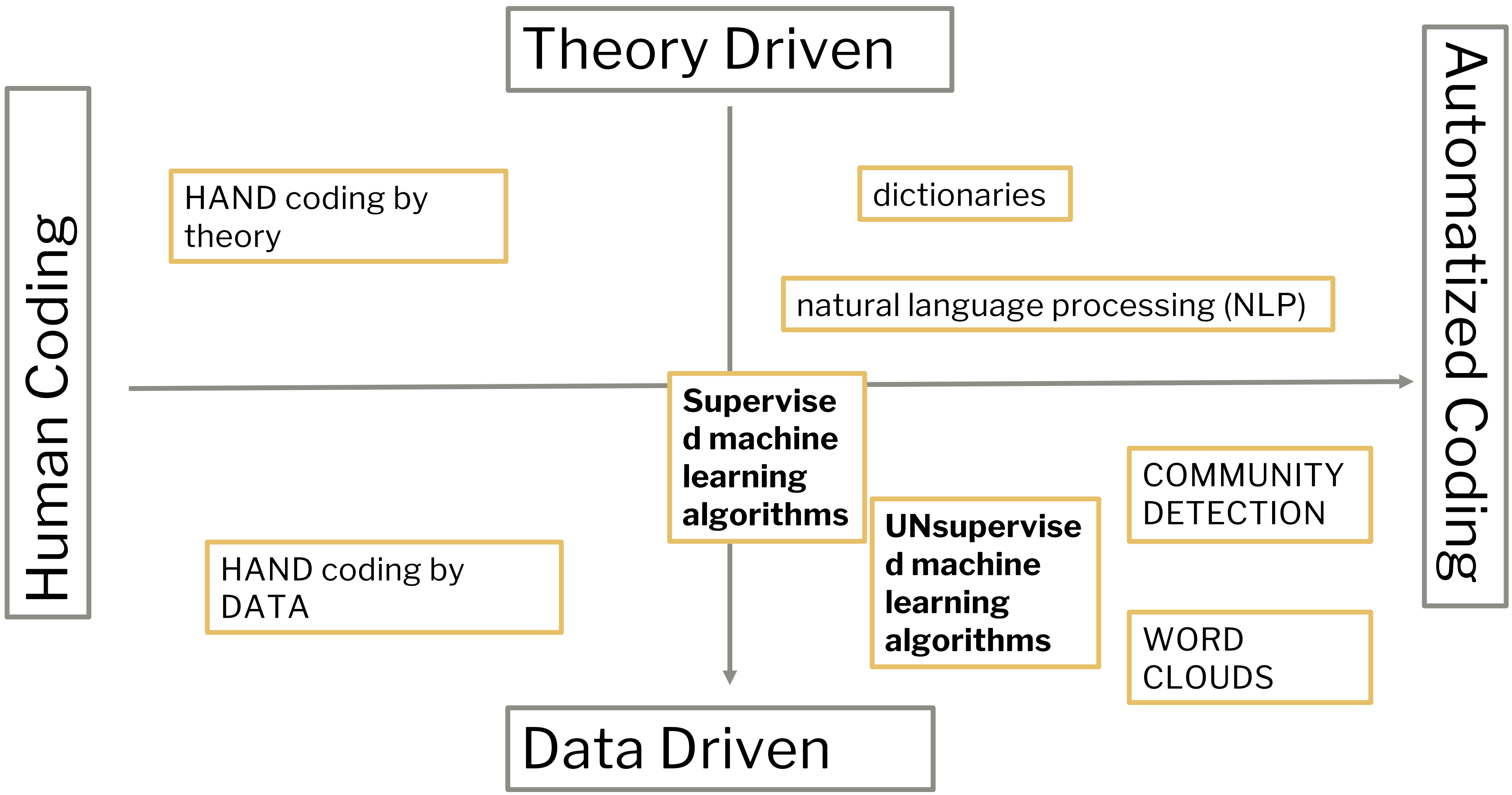
- Top down semantic/sentiment classification: bag of words
- Bottom up semantic/sentiment classification: human coding
- Meta-semantic classification: pronouns, nouns, verbs, adjectives
- Meta-semantic structural properties: word order, dropping
- Semantic & grammar: future/past/present tense

- topical signifier : shared conversation marker
- can also represent the context of a tweet
- flag an individual’s community membership
- indicate shared interests

Dealing with textual data: from text to numbers

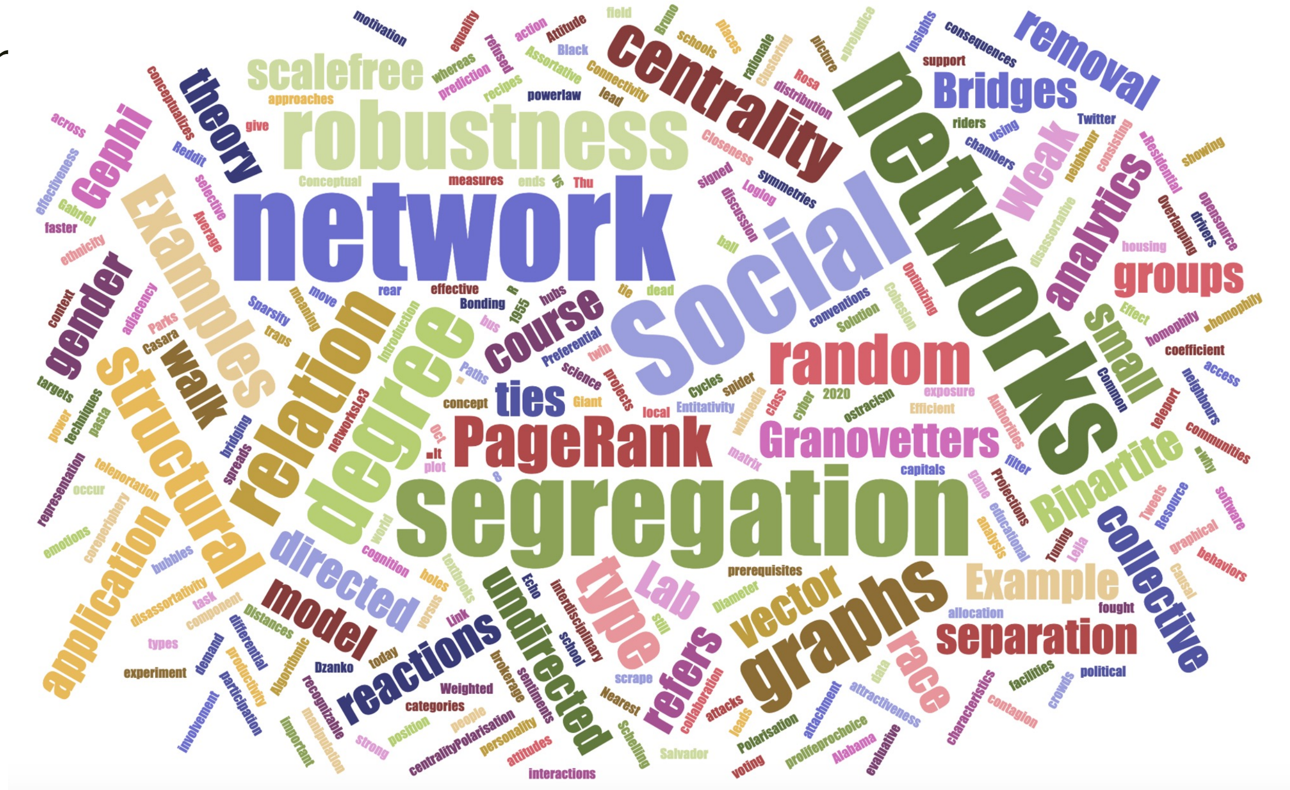


Dealing with textual data: from text to numbers



Bag of words: word cloud

- Based of word count
- Bigger words= more frequent
- bottom

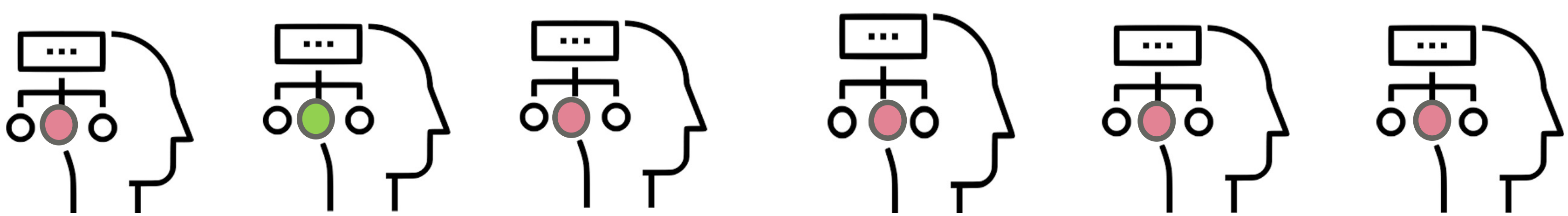


Human Coding

– *top down (coding by theory):* initial coding scheme developed from the from pre-existing theory or assumptions

– *bottom up (grounded theory):* initial coding scheme developed from the data

– *THE SUBJECTIVITY ISSUE: intercoder & intracoder reliability*
  - a classification procedure is reliable when it is consistent: Different people should code the same text in the same way



Dictionaries

- A **sentiment analysis dictionary** contains information about the emotions or polarity expressed by words, phrases, or concepts. In practice, a **dictionary** usually provides one or more scores for each word. We can then use them to compute the overall **sentiment** of an input sentence based on individual words.
- top down
- Pro: transparency, objectiveness, replicability
- contro: limited amount of words, context not taken into account

Dictionaries

- Descriptive dictionary: describe a target construct (extroversion: “gregarious,” “social,” and “approachable”)
    - Vs.
- Predictive dictionary: words that are usually used by extraverted individuals (e.g., “party,” “bar,” and “together”).

- create your own dictionary
    - Vs.
- Use a dictionary developed by other scientists
- LIWC, bing (in R), WordNet (Miller, 1990)

LIWC… *Psychometrics of Word Usage*

$109.
74

Journal of Language and Social Psychology
29(1) 24–54

DOI: 10.1177/0261927X09351676
http://jls.sagepub.com
SAGE

The Psychological Meaning of Words: LIWC and Computerized Text Analysis Methods

Yla R. Tausczik[1] and James W. Pennebaker[1]

Abstract

We are in the midst of a technological revolution whereby, for the first time, researchers can link daily word use to a broad array of real-world behaviors. This article reviews several computerized text analysis methods and describes how Linguistic Inquiry and Word Count (LIWC) was created and validated. LIWC is a transparent text analysis program that counts words in psychologically meaningful categories. Empirical results using LIWC demonstrate its ability to detect meaning in a wide variety of experimental settings, including to show attentional focus, emotionality, social relationships, thinking styles, and individual differences.

https://s3-us-west-2.amazonaws.com/downloads.liwc.net/LIWC2015_OperatorManual.pdf

LIWC

Summary Variable	
Analytical Thinking	
Clout	
Authentic	
Emotional Tone	

Informal Speech	informal
Swear words	swear
Netspeak	netspeak
Assent	assent
Nonfluencies	nonfl
Fillers	filler

With the exception of the summary variables and words per sentence, all LIWC2015 output variables are expressed as percentage of total words.

All Punctuation[5]	Allpunc
Periods	Period
Commas	Comma
Colons	Colon
Semicolons	SemiC
Question marks	QMark
Exclamation marks	Exclam
Dashes	Dash
Quotation marks	Quote
Apostrophes	Apostro
Parentheses (pairs)	Parenth
Other punctuation	OtherP

Language Metrics	
Words per sentence[1]	WPS
Words>6 letters	Sixltr
Dictionary words	Dic
Function Words	function
Total pronouns	pronoun
Personal pronouns	ppron
1st pers singular	i
1st pers plural	we
2nd person	you
3rd pers singular	shehe
3rd pers plural	they
Impersonal pronouns	ipron
Articles	article
Prepositions	prep
Auxiliary verbs	auxverb
Common adverbs	adverb
Conjunctions	conj
Negations	negate

Grammar Other	
Regular verbs	verb
Adjectives	adj
Comparatives	compare
Interrogatives	interrog
Numbers	number
Quantifiers	quant

Word count: people who is lying use more words!!!
Hancock, Curry, Goorha, and Woodworth (2008)
Extrovert people use more words (Pennebaker & King, 1999

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Fong, A., Roozenbeek, J., Goldwert, D., Rathje, S., & van der Linden, S. (2021). The language of conspiracy: A psychological analysis of speech used by conspiracy theorists and their followers on Twitter. *Group Processes & Intergroup Relations*, *24*(4), 606-623.

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With the exception of the summary variables … per sentence, a … percentage …

People who are experiencing physical or emotional pain tend to have their attention drawn to themselves and subsequently use more first-person singular pronouns (e.g., Rude, Gortner, & Pennebaker, 2004). When people sit in front of a mirror and complete a questionnaire, they use more words such as “I” and “me” than when the mirror is not present (Davis & Brock, 1975)

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With the exception of the summary variables a per sentence, percentag

STATUS Across five studies in which status was either experimentally manipulated, determined by partner ratings, or based on existing titles, increased use of first-person plural was a good predictor of higher status, and in four of the studies increased use of first-person singular was a good predictor of lower status (Kacewicz, Pennebaker, Davis, Jeon, & Graesser, 2009)

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With the exception of the summary variables and ... per sentence, ... percentag...

relationship quality

first-person plural ("we") has not been found to be related to higher relationship quality, instead use of second person ("you") is more important in predicting lower-quality relationships.
Simmons, Chambless, and Gordon (2008)

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With the exception of the summary variables and words per sentence, … percentag…

COHERENCE
Conjunctions (e.g., and, also, although) join multiple thoughts together and are important for creating a coherent narrative (Graesser, McNamara, Louwerse, & Cai, 2004).

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LIWC

People experiencing physical or emotional pain tend first-person singular pronouns (Rude, Gortner, & Pennebaker, 2004).

Emotio

Depressed patients are more likely to use more first-person singular and more negative emotion words than participants who have never been depressed in emotional writings (Rude et al., 2004)
or negative emotionality more broadly (Tackman et al., 2019) — and susceptibility to suicide (Stirman & Pennebaker, 2001)

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“we” can signal a sense of group identity, such as when couples are asked to evaluate their marriages to an interviewer, the more the participants use “we,” the better their marriage (Simmons, Gordon, & Chambless, 2005)

www.secretlifeofpronouns.com)

Psycho-social index

Affect Words	affect
Positive emotion	posemo
Negative emotion	negemo
Anxiety	anx
Anger	anger
Sadness	sad

Social Words	social
Family	family
Friends	friend
Female referents	female
Male referents	male

Core Drives and Needs	drives
Affiliation	affiliation
Achievement	achieve
Power	power
Reward focus	reward
Risk/prevention focus	risk
Time Orientation[4]	
Past focus	focuspast
Present focus	focuspresent
Future focus	focusfuture
Relativity	relativ
Motion	motion
Space	space
Time	time

Positive political ads used more present and future tense verbs, and negative ads used more past tense verbs (Gunsch et al., 2000). From the tense of the verbs and the personal pronouns used, we can infer that negative ads focus on past actions of the opponent, and positive ads focus on the present and future acts of the candidate.

Personal Concerns	
Work	work
Leisure	leisure
Home	home
Money	money
Religion	relig
Death	death

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Sadness	sad

Social Words	social
Family	family
Friends	
Female	
Male re	

Depressed and suicidal individuals are more self-focused, express more negative emotion and sometime use more death-related words.
. Depressed patients are more likely to use more first-person singular and more negative emotion words than participants who have never been depressed in emotional writings (Rude et al., 2004

Core Drives ar s	drives
Affiliation	affiliation
Achie	achieve
P	power
cus	reward
evention focus	risk
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Pasupathi, 2007
Participants were asked to either recall an event that they had discussed with someone else, or an undisclosed event past tense in discussing a disclosed event and greater present tense in discussing an undisclosed event.

Personal Concerns	
Work	work
Leisure	leisure
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Cognition & percep

LANGUEAGE AMBIGUITY (insight, tentat, Roos et al.'s (2020) is related to dogmatism (Fast & Horvitz, 2016) and politeness (Li et al., 2020).

Cognitive Processes[2]	cogproc
Insight	insight
Cause	cause
Discrepancies	discrep
Tentativeness	tentat
Certainty	certain
Differentiation[3]	differ
Perpetual Processes	percept
Seeing	see
Hearing	hear
Feeling	feel
Biological Processes	bio
Body	body
Health/illness	health
Sexuality	sexual
Ingesting	ingest

C esses[2]	cogproc
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Discrepancies	discrep
Tentativeness	tentat
Certainty	certain
Differentiation[3]	differ

Prepositions (e.g., to, with, above), cognitive mechanisms (e.g., cause, know, ought), and words greater than six letters are all also indicative of more complex language.

Cognitive complexity can be thought of as a richness of two components of reasoning: the extent to which someone differentiates between multiple competing solutions and the extent to which someone integrates among solutions (Tetlock, 1981)

Incivility score in LIWC

- Addition of Swear, Anger, and Negative Emotions (based on previous research, see Ksiazek et al., 2015; Stoll et al., 2020

Various dictionaries….

- cognitive processes (Pennebaker et al., 2015),
- moral values (Graham et al., 2009),
- psychological motivations (Stone et al., 1966),
- well-being (Ratner et al., 2019),
- regulatory focus (Kanze et al., 2019),
- markers of suicidal ideation (Thomas & Duszynski, 1985)
- brand personality (Opoku et al., 2008).

Sentiment /emotion tools

- vader_df function of the VADER package (version 0.2.1, Roehrick, 2020). VADER Sentiment Analysis. VADER (Valence Aware Dictionary and sEntiment Reasoner) is a lexicon and rule-based sentiment analysis tool that is specifically attuned to sentiments expressed in social media, and works well on texts from other domains. Sensitive to negation. Sentence level analyses https://github.com/cjhutto/vaderSentiment
- Lexicoder Sentiment Dictionary which was developed to capture the emotional tone of political communications. Young and Soroka (2012)
- integrative complexity Conway, Conway, & Houck, 2020
- EmoLex, ANEW, SentiWordNet are designed to analyze larger sets of emotional categories
- General Inquirer (GI) human curated dictionary that operates over a broader set of topics (e.g., power, weakness)
- Empath allows researchers to performtext analyses over a broader set of topical and emotional cate-gories than existing tools, and also to create and validate newcategories on demand
  (PDF) Empath: Understanding Topic Signals in Large-Scale Text. Available from: https://www.researchgate.net/publication/301872654_Empath_Understanding_Topic_Signals_in_Large-Scale_Text [accessed Nov 08 2023]. deceptive reviews convey strongersentiment across both positively and negatively charged cat-egories, and tend towards exaggerated language

WORD Net & creativity

- Word Association nets: https://wordassociations.net/en
- WordNet, a comprehensive lexical database of English words, provides a list of the cognitive synonyms associated with any concept and information regarding the links between the various words (Miller, 1998).
- Can be used to expand a dictionary
- Using such semantic networks, it is possible to approximate the **semantic distance between any two words or sentences (**although such distance measures are subject to the accuracy and completeness of WordNet itself)
- One set of studies measured creativity from the semantic distance of participant-generated ideas from a common prompt initially given to all participants (M. L. Meyer et al., 2019). Ideas that diverged more semantically from the given prompt were scored as more original and creative.

Natural language processing (NLP)

Natural language processing (**NLP**) is a subfield of linguistics, computer science, and artificial intelligence concerned with the interactions between computers and human language, in particular how to program computers to process and analyze large amounts of natural language data.

- tokenization
- grammatical role POS (part of speech) tagging (sbj, obj..)
- stemming
- thesauri
- shallow parsing : identifies constituent parts of sentences (nouns, verbs, adjectives, etc.)

  the hand-coding of a set of rules, coupled with a dictionary lookup

Machine learning

Supervised machine learning algorithms *apply what has been learned in the past to new data using labeled examples to predict future events. Starting from the analysis of a known training dataset, the learning algorithm produces an inferred function to make predictions about the output values. The system is able to provide targets for any new input after sufficient training. The learning algorithm can also compare its output with the correct, intended output and find errors in order to modify the model accordingly.*

Unsupervised machine learning algorithms *are used when the information used to train is neither classified nor labeled. Unsupervised learning studies how systems can infer a function to describe a hidden structure from unlabeled data. The system doesn't figure out the right output, but it explores the data and can draw inferences from datasets to describe hidden structures from unlabeled data.*

Content Analysis

- Detect systematic patterns in communication
  - *-> topic identification*

Sentiment Analysis

- extract, quantify, and study **affective states** and subjective information

opinions

attitudes

refers to the use of natural language processing, text analysis, computational linguistics, and biometrics to systematically identify

Topic modeling /community detection… interpretation

- “extrinsic evaluation” relies on outside sources (such as demographic variables, psychological outcomes, or annotated labels) of information to decide which topics are relevant (H. A. Schwartz et al., 2013)
- The **word intrusion task** gives testers six randomly ordered words, five of which are from a given topic. If the five words are coherent, then the intruder is easily identified Chang et al., (2009).
- **topic intrusion task** measures the model’s overall ability to describe the corpus. Given a document title, a snippet of the document, and four topics (represented by the top 8 words in the topic), the tester must identify which of the four topics was low probability for the document, versus the three high probability topics for the document.
- Or… a glance by a human over the topics! ;-)

“Open Vocabulary” approach to language analysis (H. A. Schwartz et al., 2013

patterns in language are discovered in a bottom-up manner

- correlated with dimensions of personality (Park et al., 2015),
- symptoms of depression (Guntuku et al., 2017)
- markers of schizophrenia (Mitchell et al., 2015),
- geographic distribution of variables such as “well-being” (H. A. Schwartz et al., 2013).

ANALYSE DATA

- -> frequency
- -> correlations/regressions/mediations
- -> source comparison (t-test, Anova)
- -> networks: centrality measures, community detection etc

- Boyd, R. L. (2017). Psychological text analysis in the digital humanities. In S. Hai-Jew (Ed.), *Data Analytics in Digital Humanities* (pp. 161–189). Springer International Publishing. https://doi.org/10.1007/978-3-319-54499-1_7
- Pennebaker, J. W. (2011). *The secret life of pronouns: What our words say about us.* Bloomsbury.
- Tausczik, Y. R., & Pennebaker, J. W. (2010). The psychological meaning of words: LIWC and computerized text analysis methods. *Journal of Language and Social Psychology, 29*(1), 24–54. https://doi.org/10.1177/0261927X09351676

Article

Group Processes & Intergroup Relations

G
P
I
R

Group Processes & Intergroup Relations
2021, Vol. 24(4) 606–623

DOI: 10.1177/1368430220987596
journals.sagepub.com/home/gpi
SAGE

The language of conspiracy: A psychological analysis of speech used by conspiracy theorists and their followers on Twitter

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- Social media has transformed information dissemination, often leading to echo chambers.
- **Echo Chambers**: Polarized online communities that foster conspiracy ideation.
- **Objective**: Analyze language use on Twitter by conspiracy theorists and science advocates to identify psycholinguistic patterns.

Ingroup and Outgroup Dynamics

- **Social Identity Theory**: This theory explains that people identify strongly with groups that share their beliefs, which helps to build a positive self-concept. For conspiracy theorists, the ingroup includes others who believe in similar conspiracies, and the outgroup consists of the "establishment" (scientists, governments, or other perceived authority figures).
- **Us vs. Them Mentality**: Conspiracy theorists often portray the outgroup as a dangerous, deceitful enemy that needs to be exposed or resisted. This antagonistic framing strengthens group solidarity and commitment to shared beliefs.

Psychological Needs Fulfilled by Conspiracies

- **Uncertainty and Need for Closure**: Many people turn to conspiracies as a way to simplify complex issues, especially in times of uncertainty. The need for cognitive closure—an individual's preference for certainty and definitive answers—can make simple, absolute explanations (like conspiracies) more appealing.
- **Compensatory Control Theory**: This theory suggests that when people feel a lack of control, they may seek out patterns or explanations in chaotic situations, which conspiracy theories often provide. For example, attributing complex events (e.g., pandemics) to a deliberate plan by powerful elites restores a sense of predictability and control.

Negative Emotions and Motivated Reasoning

- **Role of Negative Emotions**: Conspiracy beliefs are strongly associated with negative emotions, particularly anger and anxiety. These emotions are often directed at the perceived threats posed by the outgroup, whether it's scientists or government officials.
- **Motivated Reasoning**: Conspiratorial thinking is often reinforced by motivated reasoning, where people selectively interpret information in a way that supports their pre-existing beliefs. This helps maintain the consistency of their worldview, particularly when it aligns with strong emotions like anger or fear.

Research Goals and hypotheses

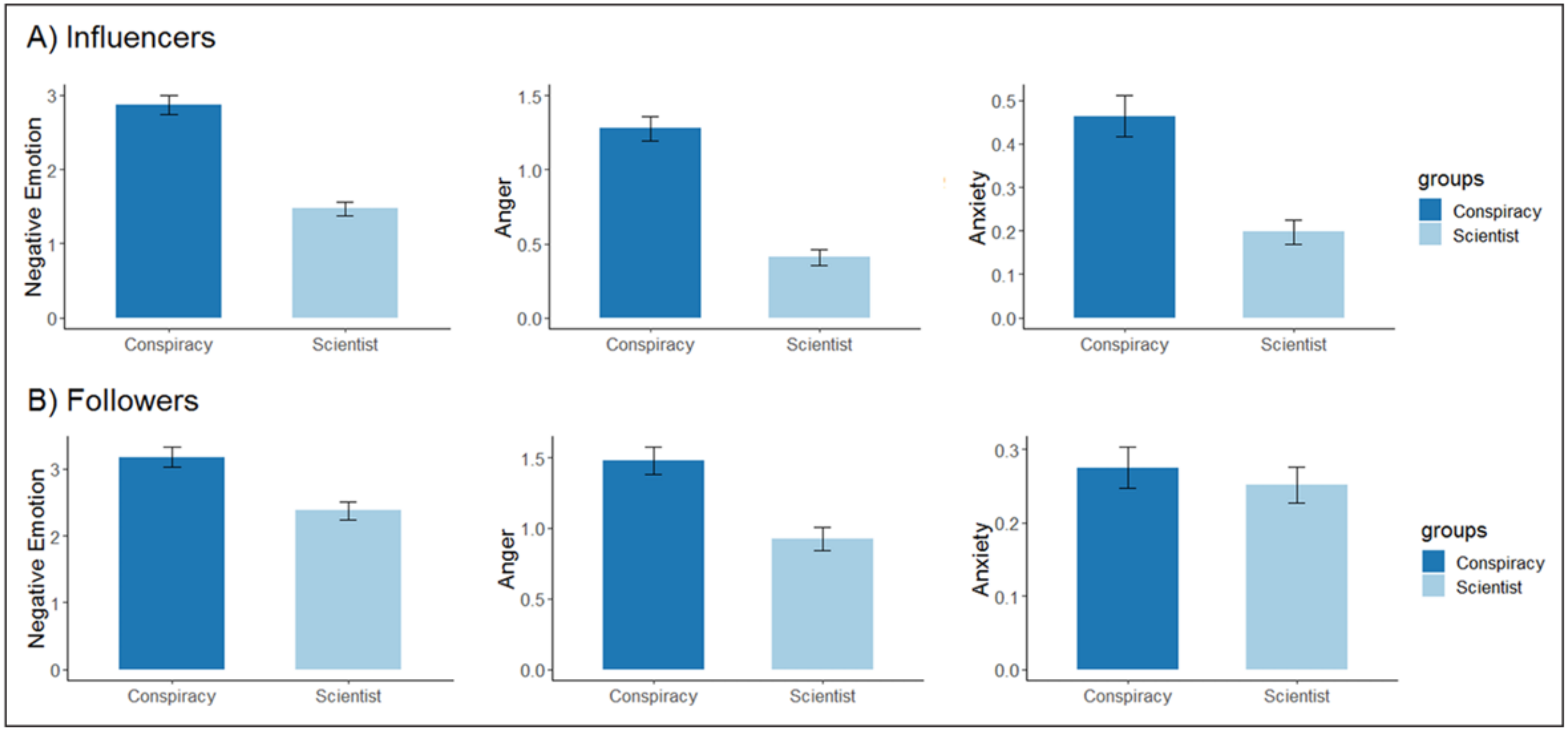
- Compare linguistic patterns in tweets by conspiracy influencers, science influencers, and their followers.
- Hypothesized psychological themes in conspiratorial speech: negativity, anger, ingroup/outgroup language, themes of power, religion, and death.

Methodology

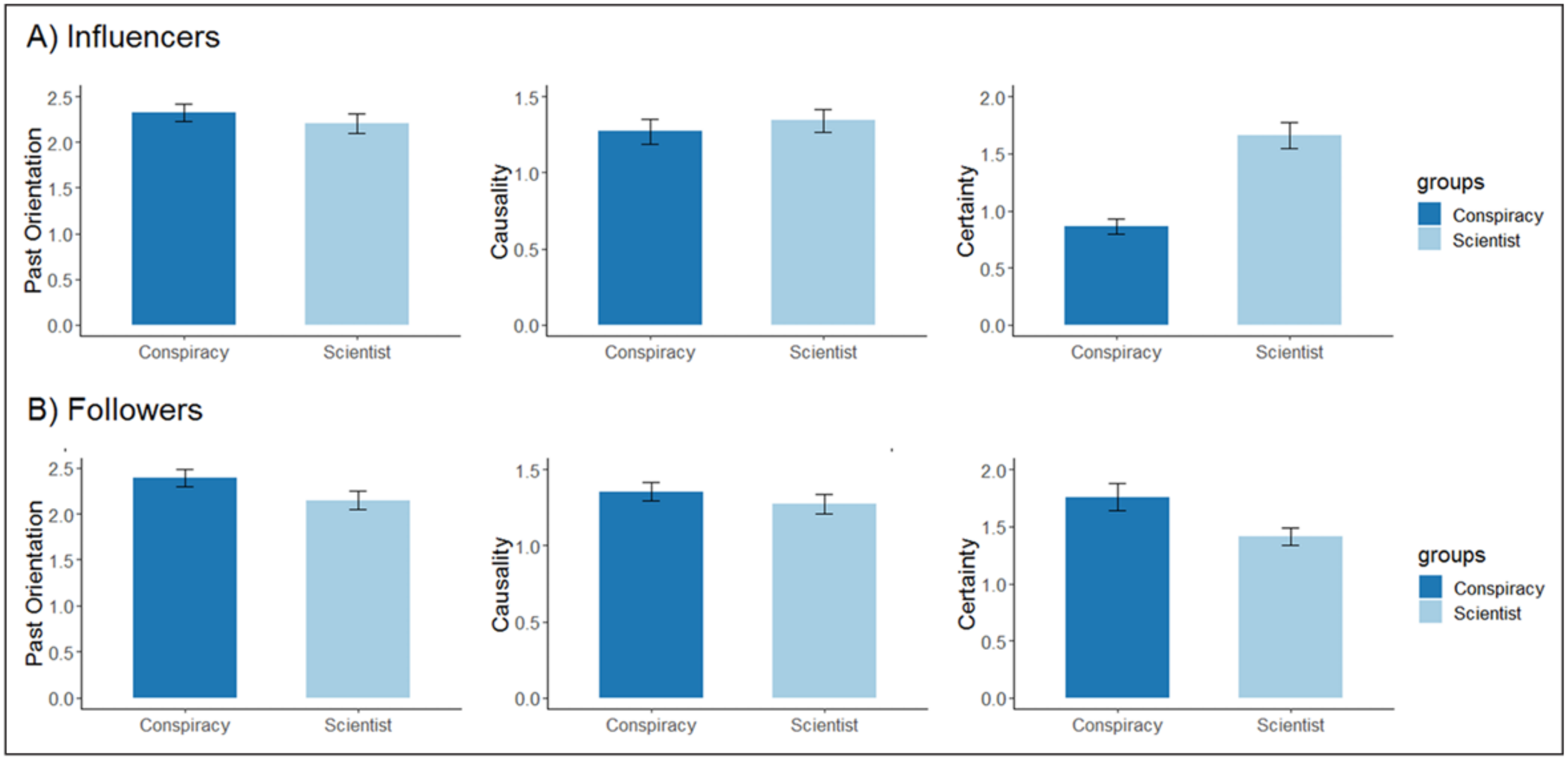
- **Data Collection**: 16,290 tweets from influencers and 160,949 tweets from followers over 5 days July 21, 2017 to July 25, 2017 posted by conspiracy theorists and science communicators who are active on Twitter (objective indicators of popularity (i.e., the highest number of followers) + random sample of followers
- **Analysis Tool**: Linguistic Inquiry and Word Count (LIWC) software to measure categories like negative emotion, cognitive processes, and thematic language.
- **Groups**: Conspiracy theorists vs. Science advocates.

Key Findings: from liwc

- **Negative Emotions**
  - **Higher Negative Emotion**: Conspiracy tweets showed more anger and anxiety.
  - **Statistics**: Conspiracy influencers scored significantly higher than science influencers in expressions of anger and anxiety.
- **Cognitive Processes**
  - Conspiracy followers displayed a higher need for certainty and past orientation compared to science followers.
  - **Unexpected**: Conspiracy influencers showed less certainty in their language compared to science influencers.
- **Ingroup vs. Outgroup Language**
  - **Ingroup Focus**: Conspiracy language reflects an “us vs. them” mentality.
  - **Follower Comparison**: Conspiracy followers used more outgroup language than science followers.
- **Themes of Power, Death, and Religion**
  - **Power**: Conspiracy tweets frequently mentioned government, military, and elite figures.
  - **Death**: Words like “war” and “killed” were more prevalent.
  - **Religion**: Conspiracy language often referenced religious terms, linking to beliefs of a “New World Order.”



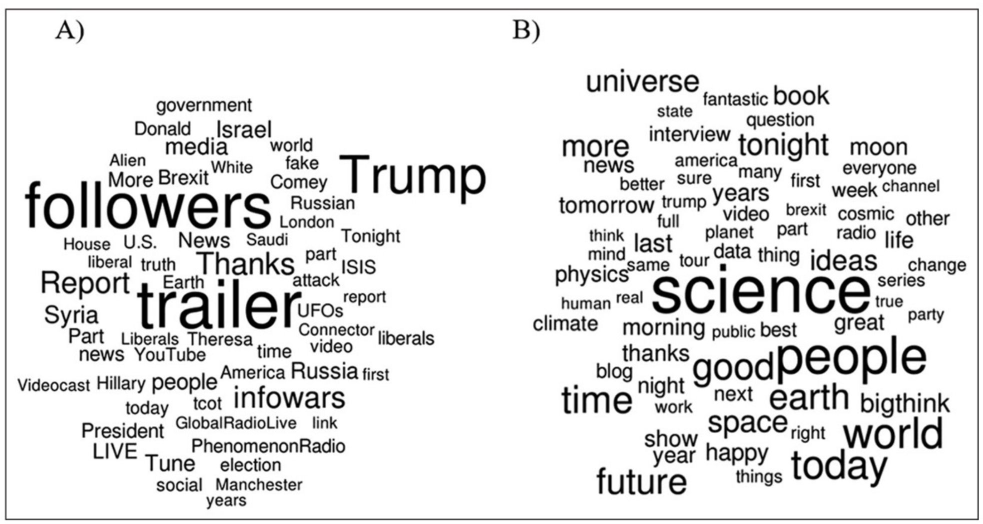
Note. Error bars represent 95% confidence intervals.



Note. Error bars represent 95% confidence intervals.

Key Findings

- Visual representation of follower networks showed clear separation between science and conspiracy followers, reinforcing echo chamber effects.



Note. Word cloud visualizing the most commonly used nouns and adjectives for the top 10 conspiracy and science influencers. Bigger and bolder representation indicates that the words appeared more frequently in the source text.

Conclusion

- Language reflects psychological states and supports an “us vs. them” framework in conspiratorial thinking.
- **Impact on Public Discourse**: Increased polarization due to conspiracy-themed language.
- **Counteracting Conspiracies**: Highlighting potential for inoculation against misinformation.
- Conspiratorial language differs significantly from scientific language, reflecting anger, uncertainty, and themes of power and death.
- Results inform strategies for combating misinformation and fostering more inclusive, fact-based discourse.

THE RISE OF #CLIMATEACTION IN THE TIME OF THE FRIDAYSFORFUTURE MOVEMENT: A SEMANTIC NETWORK ANALYSIS

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Theoretical framework

- Collective action-> any action ad-dressing a goal that surpasses individuals interest (Van Zomeren et al., 2008)

- two central psychological predictors of protest engaging:
  - *affiliation (or identity)*
  - *empowerment*

  - *+ future orientation: the tendency to foreseeing future events was positively associated to pro-environment behaviors (Sarigo¨llu¨,2009)*

Data collection

- Posts on the social media site Twitter.
- English language
- March 1st, 2017 to April 19th, 2017
- March 1st, 2018 to April 19th, 2018
- March 1st, 2019 to April 19th, 2019
- The specific choice of intervals permits capturing the semantic of climate change discourses around two main events, namely the U.S. withdrawal from Paris Agreement in June 2017, and the first Strike for Climate on the 15th of March 2018

effectively used tweets to $N2017 = 3459$, $N2018 = 4031$, and $N2019 = 3931$.

Keyword identification

- sole hashtag #climatechange to identify the most relevant hashtags connected to the climate issue in 2017, 2018, and 2019, separately.
- 20 most frequent hashtags of each year
- http://www.trendsmap.com/historical
- top ranked neutral hashtags #climatechange, #climate, #sdgs, #sustainability, #environment, #globalwarming

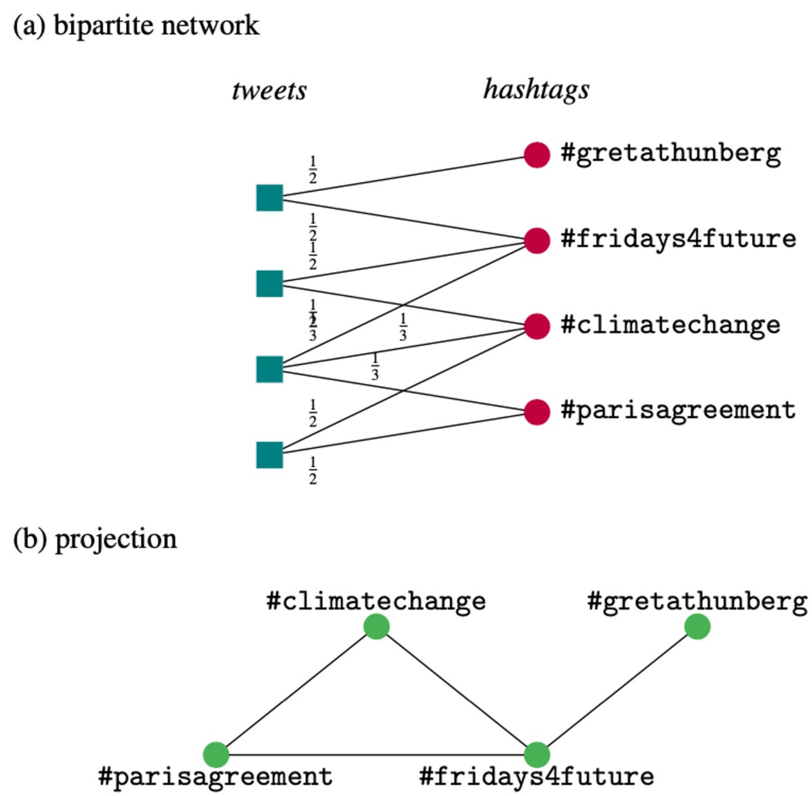
- http://www.trendsmap.com/historical

SEMANTIC CODING: application of dictionary

- **Affiliation**. The LIWC score for the category *affiliation* (e.g., ally, friend, social) was used for measuring the in- group community orientation within the text. This proved to be a reliable index of implicit motives for affiliation (Schultheiss, 2013).
- **Group-identity salience**. The frequency of personal pro- nouns can be used to assess the salience of group member- ship. In particular, the first person plural pronouns (i.e., *we*) mark the sense of belonging (Zhang, 2010).
- **Empowerment.** We computed the empowerment scores aggregating with a mean the LIWC scores for the categories *power*, *achieve*, *reward*, *insight* and *cause*.(see Decter-Frain and Frimer, 2016; Pietraszkiewicz et al., 2019)
- T**emporal perspective**.The orientation of tweets to the past or future was measured using the specific LIWC categories of *past* (e.g., ago, did) and *future focus* (e.g., will, soon).

Network building

- tweets carry the semantics content
- while hashtags (the topics) may reveal those inter-dependencies that constitute the implicit holistic information
- bipartite graph linking each tweet to those hashtags that appear in the tweet.
- Projection activates a link only between those hashtags that appear together in a tweet at least once

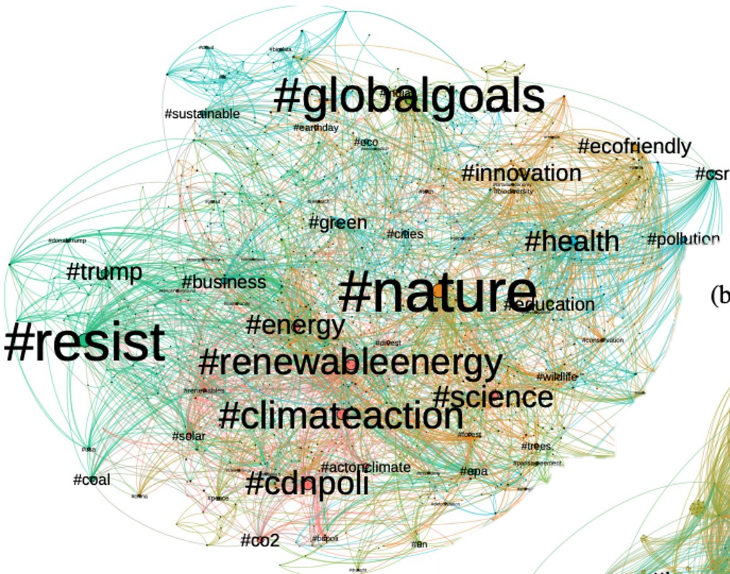


Community detection

- Louvain modularity (Blondel et al., 2008; Lancichinetti and Fortunato, 2009; Fortunato, 2010) is used to extract hashtags communities from the projected network
- A tweet will then be assigned to the community it is most similar to.

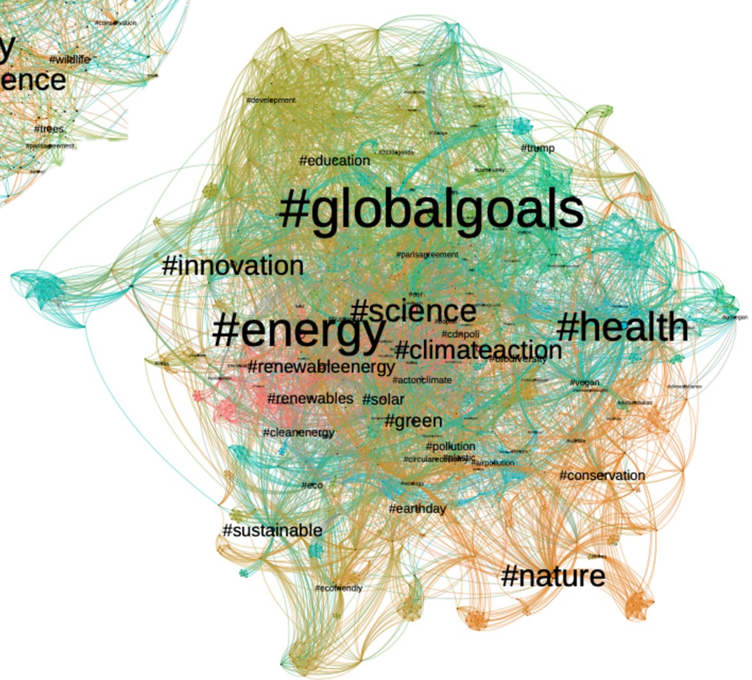
#	Community name	Descriptive hashtags	Brief description
1	climate action	#climateaction, #actonclimate, #energy, #science, #cdnpoli, #renewableenergy, #renewables, #greennewdeal, #climatestrike	calls to action related to climate change
2	nature	#nature, #earthday, #conservation, #biodiversity, #oceans, #ecology, #trees, #forests, #wildlife	photos ad videos about naturalistic environments and animals
3	recycling	#innovation, #circulareconomy, #plastic, #sustainabledevelopment, #recycling, #ecofriendly, #recycle	business solutions for the circular economy, and recycling techniques
4	work life	#leadership, #employment, #creativity, #partnerships, #decentwork, #career	professional-life and working environment aspects
5	developments goals	#globalgoals, #education, #parisagreement, #un, #2030agenda, #community, #migration, #teachsdgs	2030 Global Goals for Sustainable Development
6	green economy	#green, #eco, #sugarcane, #ecofashion, #sustainablefashion, #vegetarian	promoting green and eco-friendly products
7	international politics	#trump, #epa, #resist, #coal, #p2, #environmentaljustice, #tcot, #usa, #2a, #oil, #theresistance, #eu	political topics
8	digitalization	#ai, #iot, #dataviz, #data, #bigdata, #digital, #smartcity, #digitaltransformation, #smarthome	methods and procedures for the digital transformation and innovations
9	pollution and health	#health, #pollution, #airpollution, #cities, #healthforall, #publichealth, #wellbeing, #airquality, #worldhealthday	topics of air pollution and public health
10	lifestyle	#weather, #travel, #coffee, #worldmetday, #europe, #spring, #thursdaythoughts, #london, #sxsw, #snow, #summer, #noaa, #greenland	big variety of free-time-related topics
11	food	#agriculture, #food, #zerohunger, #foodsecurity, #regenerativeagriculture, #insect, #urbanfarming, #learn, #foodtech	food issues and food technologies
12	Australia	#auspol, #extinctionrebellion, #climatecrisis, #greatbarrierreef, #stopadani, #australia, #extinction, #factsmatter, #ausvotes, #actnowforfuture, #brisbane	climate collective actions in Australia
13	women	#genderequality, #women, #womensday, #gender, #internationalwomensday, #iwd2018, #sdg5, #unea4, #localgov, #solvedifferent, #women4climate	gender-related topics
14	green technology	#earth, #carbon, #jobs, #blockchain, #emissions, #cleantech, #engineering, #startups, #ghg, #electric, #natural, #paris, #life, #mining, #crypto	technological and sustainable innovations
15	architecture	#architecture, #fashion, #design, #construction, #greenbuilding, #building, #webinar, #steamdrills, #5star, #innovative, #free, #interiordesign	architecture topics
16	other	#agenda2030, #brexit, #news, #healthcare, #fracking, #ocean, #photography, #art, #wednesdaywisdom, #infrastructure, #climatejustice, #tourism, #mentalhealth	mixed topics

(a) Hashtag network in 2017

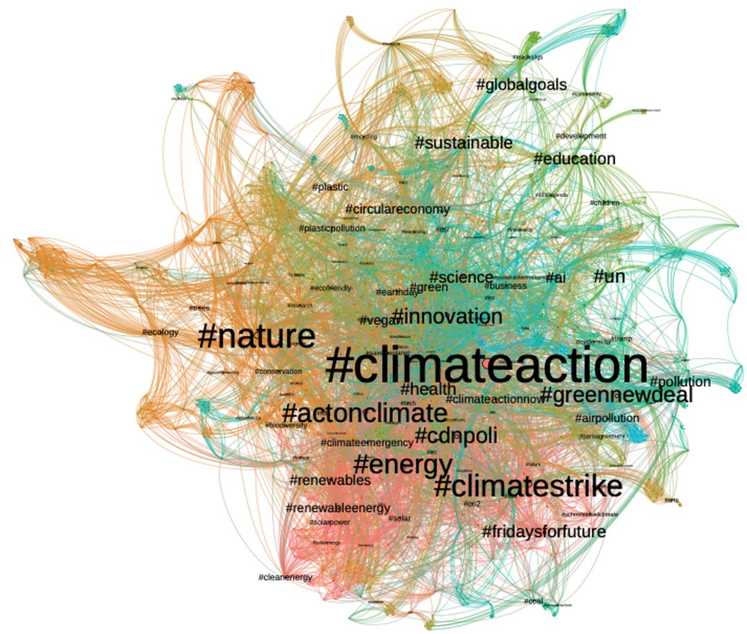


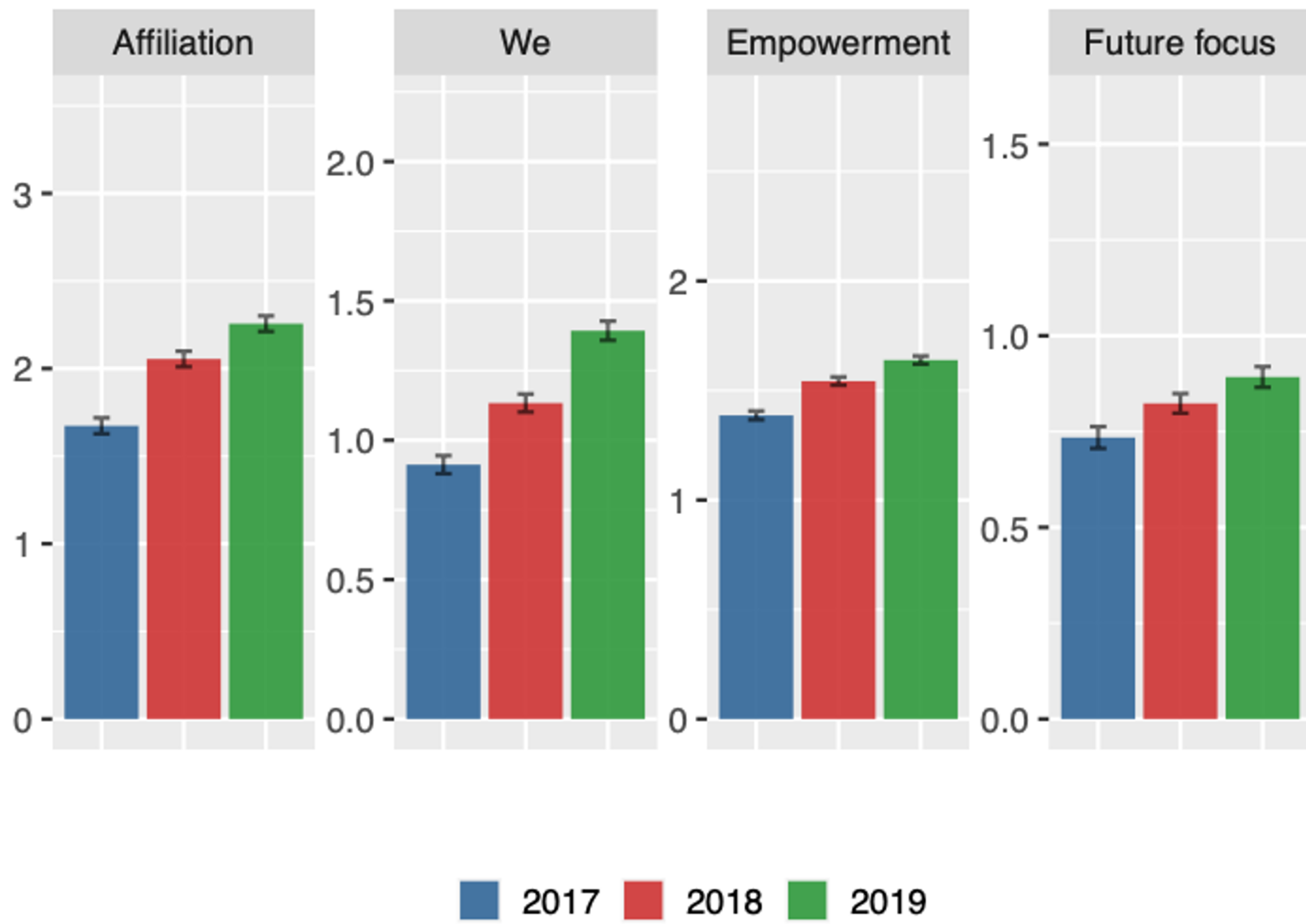
hashtag dimension corresponds to its PageRank centrality
in the corresponding year.

(b) Hashtag network in 2018



(c) Hashtag network in 2019





Affiliation
We
Empowerment
Future focus
0
1
2
3
0.0
0.5
1.0
1.5
2.0
0
1
2
0.0
0.5
1.0
1.5
2017
2018
2019

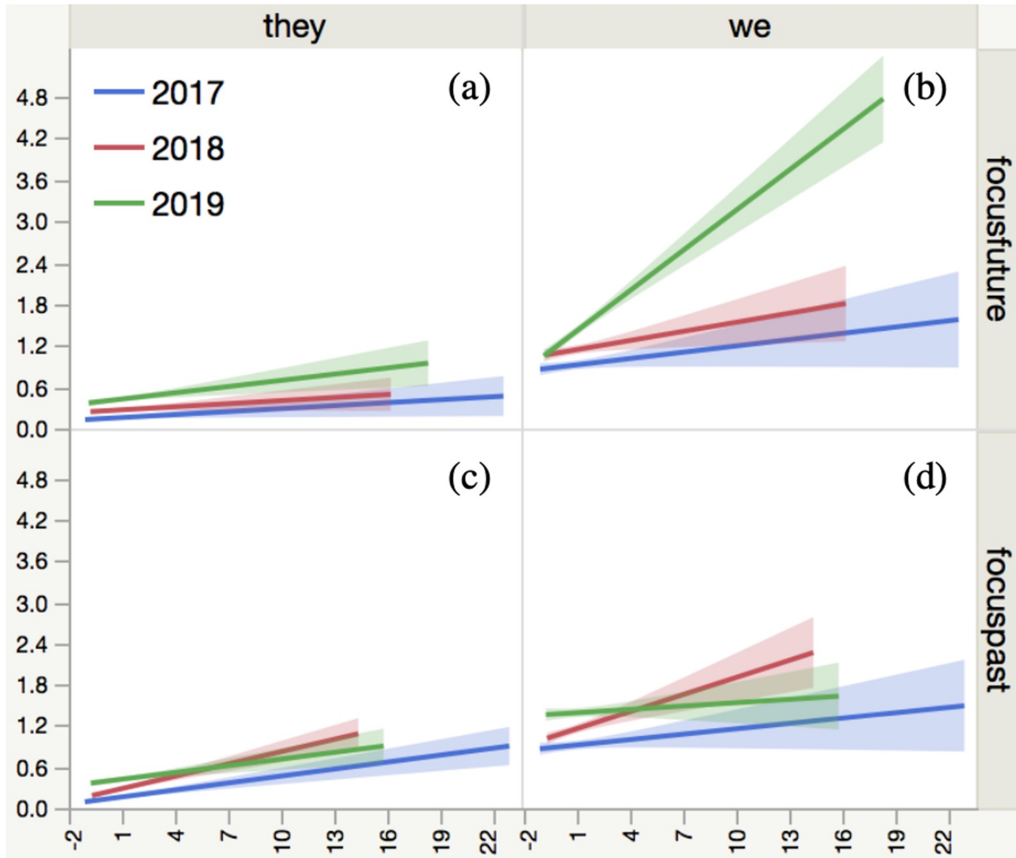
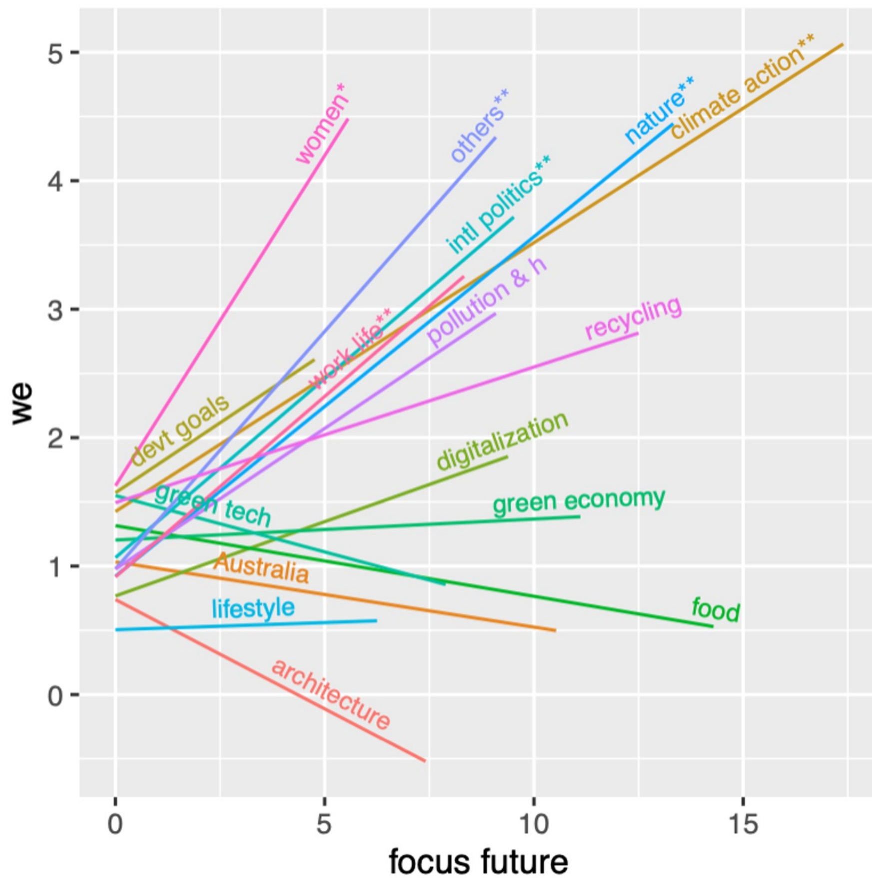


Figure 8: Linear regressions with confidence intervals over the three considered years for we/they versus past/future focus markers.

Linear regression of first person plural pronouns (we) as a function of future-framed wording (focus future) by community: an asterisk denotes a $p < 0.05$ significance of the slope coefficient, two asterisks a $p < 0.01$ significance.



- Kennedy, B., Ashokkumar, A., Boyd, R. L., & Dehghani, M. (2021). Text analysis for psychology: Methods, principles, and practices.