



This article is part of the topic “Networks of The Mind: How can Network Science Elucidate our Understanding of Cognition?,” Thomas T. Hills and Yoed N. Kenett (Topic Editors).

Cognitive Network Science for Understanding Online Social Cognitions: A Brief Review

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Received 17 December 2020; received in revised form 24 May 2021; accepted 24 May 2021

Abstract

Social media are digitalizing massive amounts of users’ cognitions in terms of timelines and emotional content. Such Big Data opens unprecedented opportunities for investigating cognitive phenomena like perception, personality, and information diffusion but requires suitable interpretable frameworks. Since social media data come from users’ minds, worthy candidates for this challenge are cognitive networks, models of cognition giving structure to mental conceptual associations. This work outlines how cognitive network science can open new, quantitative ways for understanding cognition through online media like: (i) reconstructing how users semantically and emotionally frame events with contextual knowledge unavailable to machine learning, (ii) investigating conceptual salience/prominence through knowledge structure in social discourse; (iii) studying users’ personality traits like openness-to-experience, curiosity, and creativity through language in posts; (iv) bridging cognitive/emotional content and social dynamics via multilayer networks comparing the mindsets of influencers and followers. These advancements combine cognitive-, network- and computer science to understand cognitive mechanisms in both digital and real-world settings but come with limitations concerning representativeness, individual variability, and data integration. Such aspects are discussed along with the ethical implications of manipulating sociocognitive data. In the future, reading cognitions

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through networks and social media can expose cognitive biases amplified by online platforms and relevantly inform policy-making, education, and markets about complex cognitive trends.

Keywords: Cognitive network science; Complex networks; Social media; Cognition; Online platforms; Emotional profiling; Information processing; Language modelling

1. Introduction

A key component of cognition lies in the ability to express ideas through language. Through cognition and language, concepts and emotions are retrieved from the human mind, encapsulated in words, and then diffused through written and oral media. In fact, cognition is the mental act of understanding and expressing knowledge through self-aware thought and language expression, in ways influenced by affect and personality traits (Vitevitch, 2019; Kenett & Faust, 2019; Lydon-Staley, Zhou, Blevins, Zurn, & Bassett, 2020; Murphy, Bertolero, Papadopoulos, Lydon-Staley, & Bassett, 2020). Cognition, language, and knowledge dissemination fundamentally shaped human societies over the centuries (Krippendorff, 2018). It is only in the last few decades that this process underwent some drastic changes. Online social media, mimicking friendship circles, revolutionized people's ways to speak their minds and structure their stances, knowledge, and perceptions through social discourse, timelines, and posts (Firth et al., 2019; Gallagher, Stowell, Parker, & Foucault Welles, 2019; Hills, 2019; Stella, Ferrara, & De Domenico, 2018). Social media have a strong cognitive component because they are mainly made of knowledge, that is, emotions and ideas, flowing from user-to-user along with social ties (Corallo et al., 2020; Dodds, Harris, Kloumann, Bliss, & Danforth, 2011; Hills, 2019; Menczer & Hills, 2020). This information flow is used by online users to either build or express their own experience in ways that are not fully known yet (cf. Hills, 2019).

The growth of social media usage is creating datasets increasingly larger, more complex, and more complicated to integrate (cf. Botta, Preis, & Moat, 2020; Cinelli, Quattrociocchi, & Galeazzi, 2020; Cresci, Di Pietro, Petrocchi, Spognardi, & Tesconi, 2017; Stella et al., 2018), but at the same time also more informative about language and its cognitive reflection within the human mind (Vitevitch, 2019, Stella, 2020a). Investigating social media data means achieving a better understanding of those cognitive mechanisms related to information processing, seeking, and contagion by checking the content and choices produced by millions of online users every day (Firth et al., 2019; Hills, 2019).

Social media data comes as a great opportunity but also as an open challenge. It requires modeling frameworks capable of highlighting the structure of knowledge flowing on social ties. Recently, the science of complex networks stepped up from purely social analyses and started encompassing the cognitive dimensions of social media (Del Vicario et al., 2016;

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Flammini, 2016), they did not unveil the cognitive content of such exchanges, for example, if they included specific emotions or ideas relative to aspects like hate speech or stereotypical perceptions (Hills, 2019).

The cognitive landscape of knowledge flowing along social media interactions must be investigated by language models grounded in psychology and cognitive science and thus interpretable under the lenses of cognition, personality, and behavior (Carley, 1993; Rudin, 2019). In data science, model interpretability requires transparency, that is, establishing a clear connection between the outputs of a model and its input features. Specifically, transparency and interpretability are paramount to processing and understanding natural language but are often missing in machine learning approaches (Rudin, 2019).

This review outlines concrete ways in which cognitive network science can qualitatively and quantitatively contribute to achieving interpretable investigations of language and knowledge structure in social media, crucially unveiling conceptual associations between ideas as expressed in social discourse. Cognitive network science (Siew, Wulff, Beckage, & Kenett, 2019) lies at the fringe of artificial intelligence, cognitive science, and Big Data. A *cognitive network* is a complex network where nodes represent concepts and links indicate one (Siew et al., 2019) or more (Stella, Beckage, & Brede, 2017) types of conceptual associations, for example, two words sharing the same meaning in at least one context or sounding similar to each other. Originally introduced as models of cognition almost 50 years ago (Collins & Quillian, 1969; Quillian, 1967), cognitive networks combine empirical data and theory from cognitive science. They are quantitative, large-scale representations of associative knowledge in the human mind, more specifically in the so-called *mental lexicon*, a cognitive system storing and processing ideas through conceptual associations and features of words expressible in the language (Castro & Siew, 2020; Siew et al., 2019; Vitevitch, 2019; Vivas, Montefinese, Bolognesi, & Vivas, 2020).

1.1. Manuscript outline: Five directions for social media analysis with cognitive network science

This review revolves around cognitive networks representing a key tool for understanding the meaning of words and the knowledge surrounding them through a directly accessible and interpretable map of cognitive associations (Carley, 1993). In comparison, machine learning is powerful in tagging stances or sentiment patterns (Mohammad, Kiritchenko, Sobhani, Zhu, & Cherry, 2016). However, the cognitive network approaches reviewed here are fundamentally more transparent and interpretable than black-box machine learning like topic modeling (Rudin, 2019): Cognitive networks identify not only lists of relevant/clustered concepts but also evaluate the meaningful cognitive associations between ideas as available to both text

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Unearthing the cognitive dimension of social media knowledge with cognitive networks can inform on a variety of features that are mostly left unexplored by computational social science investigations (Menczer & Hills, 2020) like:

- (i) identifying the stance of users discussing a given event, person, or idea as a network of conceptual associations, for example, investigating how online users discussed the gender gap (Stella, 2020) or social movements (Gallagher et al., 2019) could highlight potential stereotypical links/associations unavailable when investigating words in isolation;
- (ii) profiling what type of interconnected emotions were diffused by massive re-sharing of content, for example, after the lockdown release Italian Twitter users re-tweeted more messages connecting the concept of the novel coronavirus (COVID-19) mainly with other ideas eliciting predominantly fear (Stella, 2020b);
- (iii) reconstructing the flow of emotions and stances over time, providing time-evolving network structure to the narrative exchanged by users over time, for example, identifying how users promoted hateful speech with conceptual associations appearing and disappearing over time (Müller & Schwarz, 2018) or how trust appeared and vanished in the semantic frame attributed to COVID-19 vaccines over different months (Stella, Vitevitch, & Botta, 2021);
- (iv) assessing in a quantitative way how users structured their ways of thinking about specific news, with relevance for understanding about how social bots (Ferrara et al., 2016, Stella et al., 2018), fake accounts (Cresci et al., 2017) and trolls (Monakhov, 2020) influenced other users;
- (v) profile online users in terms of their digital footprint based on the language they used online, for example, assess personality traits and information-seeking patterns through network features of their language (Hills, 2019; Kenett et al., 2018; Kumar et al., 2020; Lydon-Staley et al., 2020).

This perspective article reviews the most relevant recent results on cognitive networks across the above five points. Conceptual links between the relevant literature are built in order to embed cognitive network models within the context of social media analysis, with the aim to obtain novel insights on online social cognition through sociocognitive networks. As outlined in the remainder, cognitive networks provide quantitative readings of people's minds through their language, thus leading to innovative next-generation algorithms and interpretable models capable of using social media data for grasping mechanisms like attention, perception, and memory in online settings (Hills et al., 2019; Menczer & Hills, 2020; Radicioni et al., 2020; Stella, 2020b). Particular attention is devoted also to the possibility of using multilayer networks for encapsulating within the same framework both social ties and cognitive relationships (Pietrocola & Rodrigues, 2020). Last but not least, data limitations and ethical monitoring are discussed in view of relevant research.

1.2 Cognitive networks as models of knowledge processing in the human mind

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“common” dictionary but rather represents a highly dynamical and structured system of conceptually interconnected ideas, that is, the cognitive counterpart of the language network in the human brain. Whereas experimenters could physically manipulate a human brain in the lab in order to test its connections, the mental lexicon remains a cognitive construct, whose access and testing cannot be mediated in a lab but with a strong, fascinating influence over several mechanisms of information processing (cf. Castro & Siew, 2020; Vitevitch, 2019). For this reason, the structure of knowledge in the human mind has to be investigated in other ways, like through cognitive tasks stimulating the mental lexicon (e.g., people writing about a topic) or through representations of conceptual knowledge in the lexicon itself. Cognitive networks can combine both these types of indirect access, as they can be built either through cognitive tasks or as representations of specific semantic, orthographic, phonological, syntactic, or even visual aspects of knowledge in the mental lexicon (Siew et al., 2019).

Cognitive networks were first proposed as models of knowledge in the human mind by Quillian (1967), who envisioned a hierarchical organization of concepts interconnected when sharing semantic features. Network distance on that structure could account for the time it took for participants to rate the validity of simple statements but not other patterns related to meaning negation. Given the scarcity of datasets at that time, cognitive networks were rapidly forgotten (Castro & Siew, 2020). It is only recently that cognitive networks were rediscovered, thanks to the advent of Big Data and novel theoretical tools from network scientists and physicists. Nowadays, complex networks capturing hundreds of thousands of semantic, phonological, orthographic, and syntactic similarities are increasingly successful in both descriptive and predictive models of language acquisition (Hills, Maouene, Maouene, Sheya, & Smith, 2009; Stella et al., 2017), lexical processing (Kenett, Levi, Anaki, & Faust, 2017; Kumar et al., 2020; Murphy et al., 2020, Vitevitch, 2019; Vivas et al., 2020) and cognitive degradation (Castro, Stella, & Siew, 2020).

To achieve next-generation tools suitable for processing and interpreting knowledge, it is fundamental to combine together automatic tools and cognitive models (Krippendorf et al., 2018, Mehler et al., 2020). On the one hand, cognitive science can rely on psychology and neuroscience in order to identify theoretical aspects of information processing, but it cannot test its theories without access to large-scale, longitudinal, and context-dependent datasets (Castro & Siew, 2020; Li, Engelthaler, Siew, & Hills, 2019). On the other hand, Artificial Intelligence (AI) and machine learning are proficient at spotting knowledge patterns and correlations often invisible to the human eye in large datasets (Mohammad et al., 2016), though the clear mechanisms behind such performance often lack interpretability and clear-cut cognitive grounding (Rudin, 2019). For instance, identifying positive/negative stances could be solved with high accuracy by machine learning but as a “black-box,” that is, with no insights about the cognitive structure characterizing stances themselves (Rudin, 2019).

Cognitive network science lies between cognitive models and Big Data and it shows how representing knowledge via conceptual associations can offer interpretable insights

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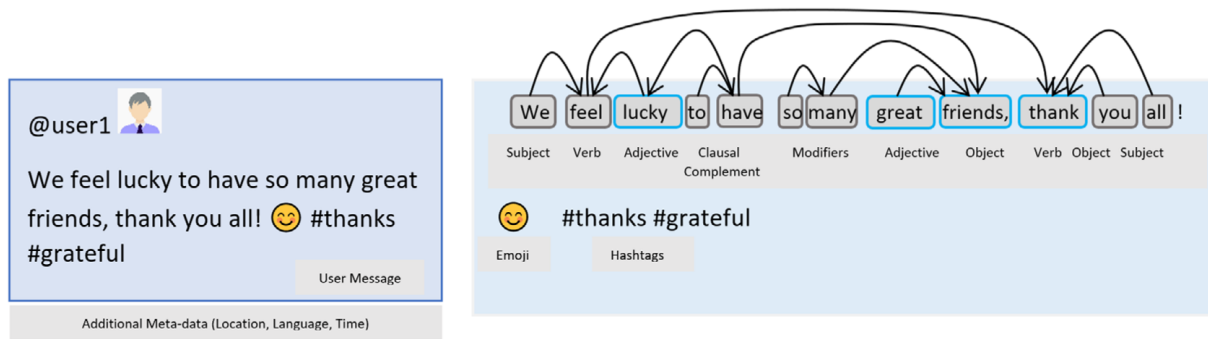


Fig. 1. When reading sentences, we do not see connections between concepts, and yet we activate these links in our minds to process meaning. Analogously, a user's post/tweet/message (left) contains syntactic, semantic, and emotional networked information (right). Cognitive networks can unveil this hidden structure of knowledge in text. Furthermore, language on social media can also include emojis and hashtags. Positive (neutral) words are highlighted in blue (gray). Syntactic dependencies and part-of-speech tagging can be reconstructed via machine learning (here TextStructure[] by WolframResearch was used) and form a complex network analogous to textual forma mentis networks (cf. Stella, 2020).

distance being interpretable through spreading activation within semantic memory (Quillian, 1967; Valba, Gorsky, Nechaev, & Tamm, 2021). These results were confirmed also in more recent investigations with multi-step experiments of conceptual associations (cf. Kumar et al., 2020).

To sum up, the above works indicate the validity and potential of cognitive networks as interpretable models of knowledge processing in the human mind. However, one might argue that knowledge in social media does not contain only words but also other elements. As reviewed in the following section, cognitive networks can be extended in order to account for the multifaceted nature of communication in social media beyond mere words.

1.3. From the mind to social media: Cognitive networks can include also emojis, hashtags, and other features of online language

The mental lexicon is used by social media users whenever they express their knowledge through online messages (see Fig. 1). In this way, language represents a powerful bridge between the human mind and the online world. Cognitive networks can capture, at the same time, the way humans express themselves and the way their minds are organized (Vitevitch, 2019).

A key issue for investigating social discourse is represented by the multifaceted nature of the massive amounts of available data (Krippendorff, 2018). For instance, only on Twitter, online users produce over 6000 tweets in 1 s (cf. Broadwater.com), and this deluge

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elements provide key semantic and emotional cues used by social users to express themselves. In particular, even though hashtags and emojis are not a language, for example, they do not satisfy grammatical rules, they can still contain relevant info. This multifaceted nature of online social media messages can be accounted for in cognitive networks, where words, hashtags, jargon, and emojis can be represented as network nodes bringing potentially different types of information (Stella et al., 2018, 2020). Hashtags can also provide information about the general topic of messages (Gallagher et al., 2018, Mehler et al., 2020) and thus enable a selection of messages around specific topics. Alternatively, hashtags and emojis can also be translated into words, enriching the overall semantic content of posts (Stella et al., 2021).

1.4. Cognitive networks reconstruct language links active in the human mind but hidden in the text

Reading sentences, much like this one, activates the mental lexicon and its cognitive structure of interconnected meanings and emotions (Vitevitch, 2019). Humans do not explicitly see conceptual associations when reading sentences, and yet they are aware of the syntactic and semantic links combining information units, for example, words, and conferring meaning and emotions to a given sentence (Krippendorff, 2018; Vivas et al., 2020). These links, present in the structure of knowledge, are mirrored in the networked structure of the mental lexicon so that language is informative of the cognitive reflection and structured mindsets of individuals (Vitevitch, 2019). Several ways for giving structure to knowledge through cognitive networks have been introduced in the past.

Word co-occurrences have been one of the first approaches detecting knowledge structure from language (cf. Ferrer-i-Cancho & Solé, 2001). Words co-occur when appearing one after each other or within a sequence of L of words. Co-occurrences are simple to compute but come at the cost of considering noise in the form of relationships with language units without intrinsic meaning (i.e., stopwords, like prepositions). Approaches relying on word co-occurrences but carefully managing (Amancio, Oliveira Jr, & Costa, 2012; Quispe et al., 2020) or removing stopwords (Stella et al., 2020) have been successful in several tasks modeling the structure of knowledge in texts. Co-occurrence networks detected key concepts in texts (Matsuo & Ishizuka, 2004), identified key aspects of social protest about COVID-19 and national lockdown in online social discourse (cf. Stella, 2020; Stella et al., 2020b), and predicted company stock prices through discussion in online forums (Colladon & Scettri, 2019). Stella et al. (2018) used co-occurrences of hashtags for exposing how accounts driven by automatic software injected hate speech in the online discourse around the Catalan referendum in 2017. Amancio and colleagues (2012) showed that co-occurrence networks highlighted dissimilarities between authors' writing styles, thus facilitating their identification. Considering multilayer networks of co-occurrences and factors shaping improved author iden-

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the development of syntactic cognitive networks (cf. Ferrer-i Cancho, Solé, R. V., & Köhler, 2004). Syntactic relationships focus on combinations of words that provide, together, a given meaning to a certain sentence or piece of text (see also Fig. 1). Extensive research has shown that the layout of syntactic links between words is indicative of a dependency distance minimization, that is, a cognitive mechanism at work in the mental lexicon and actively placing syntactically related words close to each other in sentences (Ferrer-i-Cancho & Gomez-Rodriguez, 2019). These results further highlight the cognitive relationship between the structure of syntactic relationships and cognitive patterns. Building on this cognitive interpretation, Stella (2020) enriched syntactic networks with synonym relationships in order to produce textual forma mentis networks (TFMNs), reconstructing the syntactic and semantic knowledge in texts reminiscent of authors' mental lexicon organization. Stella showed that TFMNs were capable of detecting key concepts in both annotated short texts and social media data, providing ways of capturing semantic prominence in texts beyond word frequency.

The above results open promising directions for further using networks of concepts when investigating social cognitions in online platforms. This is briefly reviewed in the following in terms of exploring cognitive phenomena related to salience, perception, and biases.

1.5. Cognitive networks enable studying the salience of words beyond frequency counts

Salience is the state of being prominent in a given context. Semantic salience or prominence characterizes concepts that are key for individuals to understand a greater extent of knowledge, and its influence over cognitive representations is a crucial research direction (cf. Vivas et al., 2020).

Social discourse can provide data useful for understanding those features influencing semantic prominence and ultimately determining key aspects of social discourse.

A key feature for identifying the semantic prominence of individual concepts through social media is frequency, that is, counting how many times a given word occurs. This metric influences a variety of linguistic tasks (cf. Vitevitch, 2019) but it is based on concepts in isolation. A word might occur more or less frequently but also always within the same context or not. Frequency alone would not be able to capture these differences. For this reason, n-grams were introduced in the literature as frequency counts of words together with other n-1 contextually related words (Damashek, 1995). N-grams can account for contextual information but also require prior knowledge on how to select words.

Keeping n fixed to 2 but considering pairwise associations among more words leads to co-occurrence networks. Further filtering out non-syntactic links leads to syntactic networks (see previous the section). In this way, syntactic networks are an extension of simpler frequency counts considering how conceptual relationships are structured across different contexts or semantic areas, that is, clusters of words with analogous semantic features (Citraro & Rossetti, 2020).

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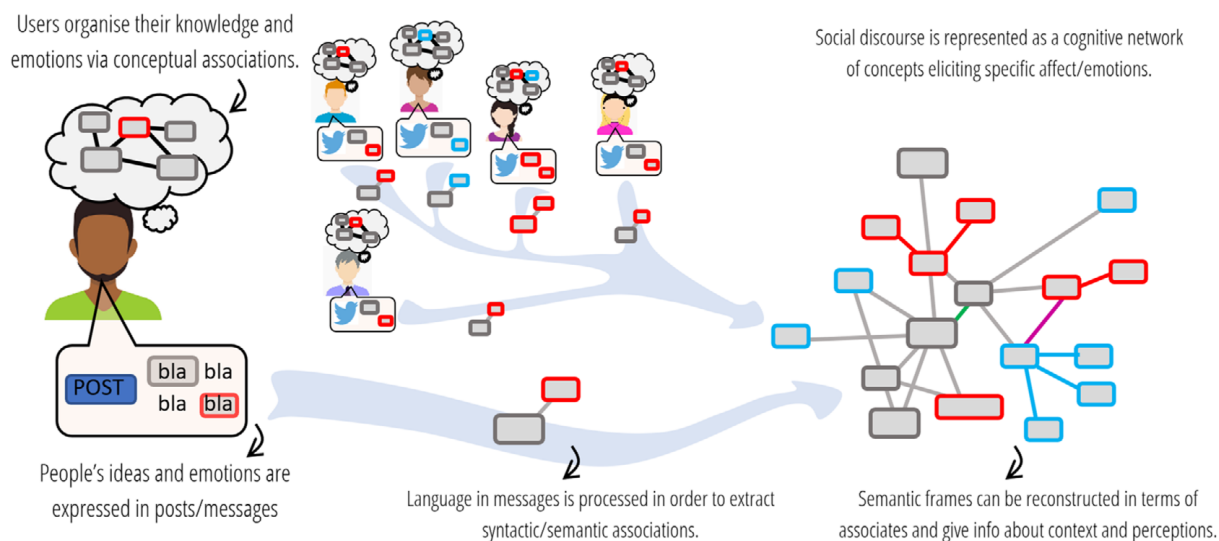


Fig. 2. Infographics about building cognitive networks out of users' messages in social media. The final cognitive network can give structure to the ideas and emotions expressed by users in social discourse as a network with links of different types (e.g., multilayer structure) and/or words expressing different emotions/sentiment (represented here by colored frames).

Stella (2020b) built on previous results of semantic relatedness/closeness being captured by semantic network distance (Kenett et al., 2017, 2018, Kumar et al., 2020) in order to model semantic prominence in terms of closeness centrality, that is, the mean network distance of one node to all its connected neighbors. The author found that frequency counts and closeness identified different classes of concepts in social discourse about COVID-19. Negative jargon, expressing social protest and complaint, was more frequent but appeared with a lower closeness centrality, that is, it was more peripheral and less well-connected across the different semantic contexts debated by users. Instead, hopeful jargon about the reopening appeared with less frequency but with a higher closeness centrality, indicating a higher structural complexity and richness of different contexts surrounding this jargon in social discourse. Importantly, word frequency was not capable of detecting fluctuations in semantic prominence that were evident with closeness centrality and which reflected news media announcements about the quarantine in Italy (cf. Stella, 2020b).

Semantic salience/prominence can be investigated also by using multiple network metrics at once, like in the study by Gallagher et al. (2018) about the #BlackLivesMatter and #All-LivesMatter movements. Through a filtering of spurious co-occurrences and local and global network metrics, the authors showed that social discourse around #BlackLivesMatter contained a richer number of semantically unrelated but salient concepts in comparison to the language in messages with #AllLivesMatter. #BlackLivesMatter displayed a more diverse

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characterizing how semantic prominence in such concepts originated. The above results call for future research in this direction, going beyond frequency measures and including accessible contextual information.

1.6. Cognitive networks reconstruct the way online users link, frame, and perceive ideas

If network structure can be used for achieving models explaining semantic salience in terms of large-scale conceptual associations, can networks and social media data assist also with the study of perception? A quantitative model for studying perception through social media data should be related to understanding how social media users perceive events through their online discussions. Cognitive networks provide a convenient and powerful way for reconstructing quantitatively the semantic patterns framing ideas on social media discourse, thanks to the theory of frame semantics (cf. Fillmore, & Baker, 2001). As also highlighted in Fig. 2, meaning is cast upon individual words by conceptual associates referring to them. For instance, a neutral word appearing in a context with negative associates might acquire a negative connotation. Semantic frame theory posits that the idea and features of a given entity (say “pandemic”) can be reconstructed by considering the other words referring to it syntactically and semantically in a given text (e.g., “people,” “infection,” “hospitals,” “populations,” “large”) (Baker, Fillmore, & Lowe, 1998; Fillmore, & Baker, 2001). Semantic frames thus surround a given word, including its related concepts, for example, people, places, and situations. In resources like FrameNet (cf. Baker et al., 1998), semantic frames are complete only when domain knowledge is made explicit, which is not always the case in social media data.

Cognitive networks can identify semantic frames as communities of tightly interconnected concepts (Citraro & Rossetti, 2020; Correa & Amancio, 2019; Ribeiro, Teixeira, Ribeiro, & de Matos, 2020) or network neighborhoods (Stella, 2020), the latter being extensively used in psycholinguistic inquiries about language processing (cf. Vitevitch, 2019). In this way, the semantic frame of a given word W can be considered either as the network neighborhood of syntactic/semantic associates of W or the network community of other words tightly connected with W and between each other. Fig. 2 reports how different semantic frames can be obtained from social media discourse.

Investigating perception could then be recast into the problem of analyzing network neighborhoods of semantic/syntactic associates around specific topics of social discourse. Pioneering results toward this direction already show that semantic frames can contain key information about the way social users discuss and perceive their experiences and beliefs. Stella (2020) found that online discourse framed the idea of the “gender gap,” usually highly criticized, in a context-rich with positive jargon, evoking emotions of joy and trust and celebrating women’s success in science. Fig. 3 reports the semantic frame (left) and emotional profile (right) of “bias” as reported by (Stella, 2020). Online users expressed

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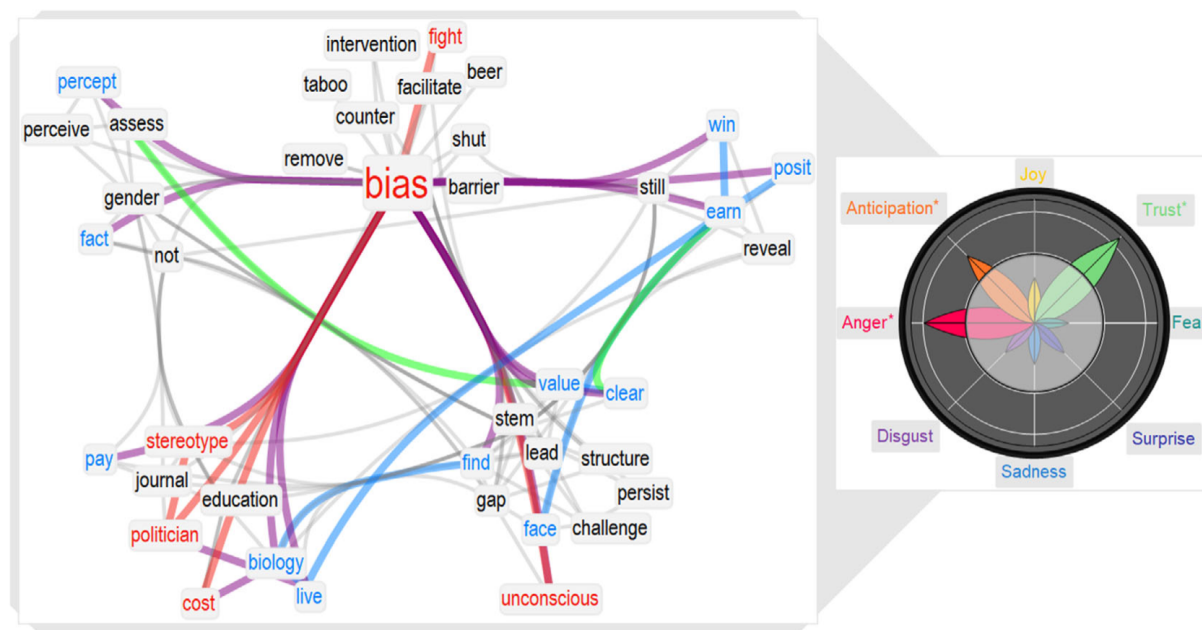


Fig. 3. Left: From social discourse about the gender gap, semantic frame of syntactic (red, cyan, and gray) and semantic (green) conceptual associations around “bias.” Semantic areas are represented as word clusters, identified through Louvain community detection. Right: Emotional flower, reporting the z-score of the observed number of words eliciting a certain emotion in comparison to random expectation. Petals falling outside the white circle indicate z-scores higher than 1.96, that is, emotions stronger than random expectations (cf. Stella, 2020).

Semantic frames could be reconstructed also in terms of network communities, as suggested by recent work including linguistic features in community detection analysis and identifying coherent semantic frames from cognitive network data (Citraro & Rossetti, 2020). Also, Radicioni and colleagues (2020) identified semantic frames as communities, in hashtag co-occurrence networks. The authors reconstructed how users with different political views semantically framed the Italian elections in 2018. Media coverage was found to strongly polarise frames, enriching them with jargon either strongly supporting or deeply criticizing political figures. Such influence might be explained by the great deal of public attention directed toward online media coverage as recently found in (Perra et al., 2020). The above pioneering results indicate that the investigation of semantic frames on social media can capture the cognitive influence exerted by news media over polarising social users or altering their perceptions, a crucial yet relatively unexplored research field.

Reconstructing semantic frames from syntactic/semantic dependencies in text is an important task also for unearthing how concepts are structured and promoted by fake news and misinformation channels in the “dark side” of information flow (Hills, 2019). In their investigation of conspiratorial theories and the 5 C on Twitter, Ahmad and colleagues (2020) found

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& Ceri, 2020) but not on other social media platforms (Cinelli et al., 2020), detecting online controversial content calls for additional consideration of the cognitive dimension of users' semantic frames within future research. Attention should be devoted to going beyond resharing counts, understanding the ways information is cognitively perceived, framed, and subsequently diffused (Stella et al., 2021).

Investigating semantic frames is important also for monitoring aims, like identifying the overall wellbeing and mental health of large audiences (Linthicum, Schafer, & Ribeiro, 2019). Cognitive network science has already been used in investigations related to mental health. Forbush, Siew, and Vitevitch (2016) used cognitive networks for reconstructing the symptoms expressed by people with eating disorders. The authors gave structure to the correlations between symptoms as expressed by 143 individuals and found "body checking" as the most semantically prominent, that is, a key symptom to act upon for enhanced cognitive-behavioral therapies. Analogously, a recent textual analysis of 139 suicide notes showed that "love" and "life" are key to those who commit suicide, although the latter framed such words with drastically different sets of emotions when compared to mind-wandering in absence of suicide ideation (Teixeira, Talaga, Swanson, & Stella, 2020). These network-powered results are promising in identifying novel features of texts and posts for better identification of mental health issues in social media posts (see also Linthicum et al., 2019).

1.7. Cognitive networks can profile online users according to conceptual associations in their posts

The cognitive dimension of messages is key not only for investigating people's perceptions but also for studying salient features of users' minds like attitudes or personality traits, which all contribute to the creation of a "cognitive fingerprint" identifying how individuals reason and behave through associative networks (cf. Abbas et al., 2020). Cognitive network science has shown that giving structure to knowledge can uncover patterns of relevance for cognitive abilities like creativity (Kenett & Faust, 2019; Kenett, Anaki, & Faust; 2014, Mednick, 1962) and personality traits like curiosity (Lydon-Staley et al., 2020) and openness-to-experience (Christensen, Kenett, Cotter, Beaty, & Silvia, 2018).

Generally speaking, creativity is the ability to draw connections among apparently unrelated concepts, filling gaps in knowledge or finding new ones (Mednick, 1962). Several recent works have shown that the structure of knowledge in the mental lexicon is linked with the levels of creativity in populations (Benedek et al., 2017; Kenett et al., 2014; Valba et al., 2021) and individuals (Kenett et al., 2018). For instance, Kenett et al. (2018) showed that individuals with a higher creativity possess a semantic network with enhanced connectivity, that is, shorter path lengths between couples of connected concepts and an overall less pronounced community structure. The authors argued that such organization of conceptual associations could facilitate search processes for linking novel combinations of ideas. A scale

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weaker conceptual links, connecting different semantic communities. These studies indicate that people with a higher creativity can navigate their knowledge in different ways, compared to people with lower creativity, and this difference can be found in language. Reconstructing semantic/syntactic networks in social media, potentially through TFMNs (Stella, 2020a), would therefore open concrete, quantitative ways for novel research directions where the creativity of online users is estimated by simply considering their messages, calling for future research endeavors.

In a similar fashion, also personality traits might be estimated from users' language, like openness to experience (Christensen et al., 2018; Christensen, Cotter, & Silvia, 2019) and curiosity (Lydon-Staley et al., 2020). Openness to experience identifies people's willingness to embrace change, to be intellectually curious, and open-minded. This definition was provided by Christensen et al. (2019) through a network community analysis over different taxonomies used for measuring openness itself. Like for curiosity (Kenett et al., 2014), individuals with a higher openness to experience exhibited a different organization of associative knowledge in their mental lexica in comparison to people with lower openness (Christensen et al., 2018), thus opening new research opportunities for studying openness to experience in online contexts thanks to social media data and cognitive network science.

A different approach could be used for determining individuals' curiosity, a tendency to seek information due to multi-faceted feelings of deprivation (Lydon-Staley et al., 2020). The recent study by Lydon-Staley et al. (2020) built semantic networks out of Wikipedia webpages visited by individuals who were also monitored through self-assessed surveys. Participants with a strong drive to know and eliminate gaps in their knowledge ended up building considerably more tightly interconnected semantic networks than other individuals with a lower sense of curiosity. Also, different behavioral patterns of information seeking and network navigation were found. Individuals tended to either revisit concepts many times, intensifying local conceptual associations (hunters), or explore knowledge by jumping across different semantic areas (busybodies). Understanding how people revisit concepts in subsequent messages (e.g., a Twitter timeline) in a way similar to (Lydon-Staley et al., 2020) might provide additional cognitive footprints about curiosity and information seeking mechanisms. An analogous procedure considering only conceptual revisiting of the same concepts and semantic areas in tweets was introduced by Monakhov (2020) for detecting trolls, that is, users inflaming social discourse with abrasive language and influencing even massive voting events or public perceptions (Broniatowski et al., 2018). Monakhov (2020) showed that trolls tend to behave like Lydon-Staley et al.'s "hunters," revisiting only a limited span of conceptual associations, a feature that was used for detecting trolling with an accuracy of 91% but using only 50 tweets per user.

1.8. Cognitive networks open the way to sociocognitive investigations of online ecosystems

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representation. Besides TFMNs (Stella, 2020, 2020b), as described above, other cognitive approaches with multilayer networks were recently introduced in the literature. Conceptual distance in multilayer networks (combining phonological, categorical, and semantic associations) was found to be predictive of both normative word acquisition in children (Stella et al., 2017) and picture naming failures in people with a spectrum of aphasic disorders (Castro et al., 2020). Combining phonological and orthographic similarities in a phonographic multilayer network, Siew & Vitevitch (2019) showed that network degree predicts a facilitatory effect for visual word recognition absent in single-layer networks. By connecting topics according to semantic/syntactic similarity, Mehler et al. (2020) introduced *multiplex topic networks*, which highlighted a stronger co-occurrence of geographically distant places featuring analogous semantic features in online social discourse.

For their ability to capture different types of links among the same or potentially different groups of nodes, multilayer networks possess the potential to model both social and cognitive interactions among users. An example is Pietrocola and Rodrigues's work (Pietrocola & Rodrigues, 2020), which combined networks of conceptual associations with networks of social interactions. In a classroom setting, the authors showed that students connected by stronger social ties also exhibited similarly structured conceptual networks around the topics of classroom life. Such correspondence between similar knowledge and stronger social ties in social media relates to echo chambers, that is, groups of actively interacting online users with the same stance (Cinelli et al., 2020; Del Vicario et al., 2016). In turn, echo chambers are caused by confirmation bias, that is, a cognitive tendency for the human mind to simplify the acquisition of low-quality new knowledge by adjusting it to a pre-existing set of beliefs and info (Hills, 2019). Overloaded by brief and often incomplete information (Qiu, Oliveira, Shirazi, Flammini, & Menczer, 2017), online users end up being more susceptible to confirmation bias and thus acquire mostly information already suiting their pre-existing knowledge (Hills, 2019). These mechanisms can generate different classes of more or less connected social users differing in their knowledge structure and emotional portrayal of news, thus motivating sociocognitive investigations of social ties and cognitive networks. Multilayer networks would account for both such types of network structures and open novel quantitative scenarios for the investigation of social cognitions within such echo chambers.

2. Discussion and open challenges

Beyond the methodological gaps and research opportunities outlined above, the framework of cognitive network science for investigating cognition through social media poses also important meta-research advantages and limitations.

The main advantage of cognitive networks is their intrinsic ability to provide mappings and quantitative metrics that can be interpreted from a cognitive perspective (Siew et al.

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through cognitive networks can greatly benefit several research lines studying cognition like semantic framing, stance detection and perception, emotional dynamics, and cognitive biases as outlined above.

Cognitive networks can be powerful assets also for exploring the cognitions portrayed by AI-driven accounts like social bots (Ferrara et al., 2016). Often posing as human accounts, social bots are driven by automatic code and promote human-like content so that the above network techniques would work also for better understanding what social bots do (Menczer & Hills, 2020). By considering cognitive networks of hashtag co-occurrences and networks of social interactions combined, (Stella et al., 2018) found that social bots mainly targeted influential human users and introduced hate speech in specific online groups. Characterizing the structure of knowledge promoted by social bots through cognitive networks represents a key way for unveiling how automated accounts can manipulate human users, human perceptions, and information seeking behavior (Broniatowski et al., 2018; Ferrara et al., 2016; Hills, 2019; Menczer & Hills, 2020).

Cognitive networks can also enable novel ways of profiling users according to their language as discussed above. These pioneering approaches are promising but pose important limitations in terms of representativeness, variability, and integration. Social media can give voice to large audiences but not to everyone, as it is increasingly clear that only certain demographic groups access online platforms, for example, older people with a lower income tend to tweet less than younger professionals (Brandwatch.com). This poses important limitations to the extent to which social media inquiries provide access to data sufficient enough for fully characterizing both global perceptions and individual users. Related to this issue, there is individual variability. Although sometimes users achieve consensus and provide a normative, average perception representative of the whole group (Cinelli et al., 2020), this is not always the case. Even at the individual level, a person might display flickering emotions (Stella, 2020b), change their language over time (Dodds et al., 2011), or across different platforms/social contexts (Cinelli et al., 2020). This underlines the importance of integrating data from multiple sources, providing monitoring tools that sample across different platforms and over time in order to read individual users' mindsets in their online social environments. Preliminary results with trolling (Monakhov, 2020) indicate that little individual data is required for profiling some users' behavior, but additional research about personality traits and social media is required. It should be noted that increasing the amount of data relative to individual users, potentially coming from different social media platforms, would facilitate the construction of cognitive networks modeling individual cognitions. On the one hand, this would match current efforts in moving from group-level to individual semantic networks for devising longitudinal results accounting for individual variability over cognition. An example is using individual semantic/phonological networks for capturing how individual children acquire language over time (Beckage & Colunga, 2019). On the other hand, individual cognitive networks would reflect the way of thinking of individual users, reconstructing and highlighting

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In fact, ethics is paramount for the application of cognitive network science to social media analysis. Users adopt the online world often as a way to communicate and find meaning in their own personal lives, a phenomenon that has been studied for decades by narrative psychology (László, 2008). If online users exploit their own and others' narratives in order to deal with experiences, gathering their online data even only for research purposes might represent a violation of a delicate personal space. The possibility of accessing someone's mind and personality through their social data poses novel risks for privacy. Would it be ethical for a research institution to gauge online audiences, read their ways of thinking through cognitive network science, and perform business predictions about, say, the job market without explicitly asking for consent from the users themselves? Considering confirmation bias, information pollution produced by social bots, and misinformation campaigns (Hills, 2019), would the patterns extracted through cognitive networks be suitable for commercial purposes, or would they rather be distorted by online biases and social-bot manipulation (Menczer & Hills, 2020; Stella et al., 2018)? These scenarios call for additional future research within specific ethical boundaries, guaranteeing the confidentiality, respect of anonymity, and minimizing chances for social manipulation. Reading people's minds through networks calls for new research opportunities but also for additional ethical efforts for protecting human users and their privacy. Cognitive-, data-, social- and network scientists should contribute to the quantitative development of cognitive networks for studying cognition through social media data. However, these scientific figures should also work together with philosophers and law experts under the umbrella of complexity science in order to provide clearer indications for an ethical growth of this whole new field, taking inspiration from recent efforts in organizational psychology and network science (Cronin et al., 2020).

Social media data and cognitive networks can revolutionize current models and understanding of cognition across the areas concretely outlined here. This opens to a brave new world of opportunities for a new generation of researchers bridging different fields and pioneering whole new ways of reading, understanding, and even predicting people's ways of thinking through digital media.

Acknowledgments

The author acknowledges Prof. Daniele Marinazzo for stimulating feedback.

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