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Theory-Building and Tool-Building for a Science of Dysfunctional Political Discourse

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Abstract. This paper extends a developing analytic framework for political discourse that takes place over digital social media. Earlier presentations of the framework have furnished a rationale for applying the conceptual framework of epistemic frame theory and the tools of quantitative ethnography for political discourse analysis. They have provided early existence proofs of the viability of epistemic network analysis (ENA) for rudimentary models of social media threads that involve political content. The current theoretical paper moves significantly beyond this foundation. It summarizes and deepens the explanation of the constructs of discursive transactions, response grammars, and epistemic frames in political discourse. It proposes and supports three modeling tools for building a productive science of political discourse. The first modeling tool involves both ENA and a mathematical means for extending ENA's key explanatory and predictive potential to display dyadic connections between constructs. The second involves complex adaptive system (CAS) theory. The third involves the application of artificial neural networks. Each of these three tools provides valuable modeling affordances which the other two do not. Collectively, these three approaches hold promise to contribute to the science of political discourse by deepening our understanding and supporting potential repair of profoundly disturbing trends in political conversations that are unfolding globally.

Keywords: quantitative ethnography · epistemic network analysis · epistemic frames · political discourse · artificial neural networks · complex adaptive systems · parallax

1 Introduction and Purpose

This theoretical paper extends an analytic framework [1, 2] for political discourse that takes place over digital social media. It is intended as a prospectus for the challenge of building a more robust science of dysfunctional political discourse analysis. In the US and in other countries, dysfunctional or polarizing discourse has become a ubiquitous, ominous reality. Political discourse is a critical mediator for how a society sets priorities, deliberates over, and responds to urgent social issues. Yet especially when

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conducted over social media, political discourse has fallen into widely-recognized dysfunction, characterized by increasing and self-reinforcing [3] anti-social norms of incivility, disgust, and polarization. That dysfunction sabotages the public policy processes that effective problem-solving and innovation require, imposing harsh, immeasurable setbacks to societal well-being and progress. Because dysfunctional discourse appears intractably resistant to obvious corrective measures, it merits serious analysis to uncover non-obvious patterns, connections, or structural properties. The goal of repairing political discourse seems only possible with the benefit of such targeted analyses.

Political discourse analytics have already found a growing niche in discourse analysis research more broadly, especially in the areas of narrative networks and bipartite analysis [4–6]. This paper adds to that broader literature by explaining how three interpretations, or modeling tools, of quantitative ethnography (epistemic network analysis, complex adaptive systems, and artificial neural networks) may separately and collectively yield explanatory and predictive models of political discourse, and may reveal tipping points beyond which productive discourse is statistically likely to worsen monotonically. As a theoretical paper, we offer it as a precursor to planned empirical and simulation studies that encompass myriad dynamic patterns and variables, studies designed to help build a productive science of dysfunctional political discourse.

Our primary goal in contributing to a science of dysfunctional discourse is to help foster discourse repair. Dozens of initiatives underway seek to do just that [e.g., cataloged in 7], through complementary approaches that address different aspects of what can be considered dysfunctional discourse pathology. Among such complementary approaches, this paper takes a theory-driven models and modeling perspective [8] to explore a view that humans, with views across political spectra, are highly vulnerable to false but avoidable polarization -- polarization that both a) sabotages the relational richness necessary to build social trust, and b) metastasizes by feeding on itself, thus iteratively catalyzing further depletion of social trust.

A possible foundational implication of visualizing the pathology of polarizing discourse is recognition that virtually every aspect of how individuals view others acrimoniously through the lens of political beliefs may be fundamentally unsound and flawed. That is the essence of the semantic parallax argument advanced in an earlier paper [2], that the meaning of *what* we see is distorted by the *ways* that we see – what we later refer to in this paper as our affect-intense epistemic frames. And because actions inexorably shape personal identity, *acting* on what we *think or believe* we see in one another can intensify the parallax, distorting us individually and collectively – unintentionally cultivating persona shifts that are artifacts of dysfunction but seem to validate negative views that political opposites have of one another. That parallax then recycles distortion to further damage social trust, collective identity, and national viability.

The modeling tools this paper suggests take on the difficult challenge to make such parallax and the dynamics it enmeshes visible in the following way. Models that can plainly depict polemics and response patterns used by different political groupings, and the subsequent divisions such patterns spawn in broader societal discourse, might illuminate unintentional but recurring traps – traps that misdirect discordant affect and attention, and thus subsequently erode civil discourse. We also expect to identify potential opportunities for repairing gaps in the verbal communication structure deployed by antagonistic participants engaged in hostile political dialog.

Each of the three types of modeling tools – epistemic network graphing, complex adaptive systems, and artificial neural networks – has different affordances and tradeoffs (summarized in Table 3) for making visible pathological aspects of dysfunctional discourse and its self-reinforcing nature. The next section outlines constructs that form a common language applicable to each of the three modeling approaches. The paper then reviews the potential viability of each approach and its tradeoffs.

1.1 Five Constructs: Epistemic Frames, Discursive Transactions, Response Grammars, Cognitive Appraisal, and High-Valence Activations

Five important constructs apply to each of the three tools the paper proposes for building a productive science of dysfunctional political discourse.

As noted elsewhere [1], the construct of **epistemic frames** [9] provides both language and a means to integrate important considerations underlying political discourse. Epistemic frames refer to "everything" that is involved in an individual's mindset – in this case, narrowed to a political mindset (qualifying that the term "mindset" includes considerations of emotion central to the study of dysfunctional discourse). The terms "political epistemic frame," "political point-of-view (POV)," or simply "epistemic frame" appear interchangeably here as a reference to an individual's political perspective. A political epistemic frame thus represents a holistic, dynamic, and multifaceted emotional and cognitive construct. It incorporates moral commitments, personal understandings, the impact of personal experiences, political interactions, prejudices, self-interest, and a sense of personal identity and identity protection – the totality of interconnected attitudes towards politically related attitudes and individuals. This theory-building and tool-building research centers around epistemic frames, how they are expressed. And how they change during socially-mediated political discourse.

Table 1. Sample Response Grammar Scenario

Representative X is attacked on social media by Candidate Y, running for the same office, for using taxpayer money to buy votes on a certain spending bill. In this example, X knows that by supporting the spending bill, s/he is doing exactly that - using taxpayer money to buy votes. X also knows that the spending bill will do some good – besides making it more likely s/he will get elected – an easy win-win situation. But X also believes that it may not be a very judicious use of taxpayer money, and it kicks the can down the road for resolving a looming fiscal crisis. X has a complex response that attacks Y by sarcastically belittling the original complaint, attempting to diminish Y's overall political philosophy, and raising questions about Y's suitability for office

How epistemic frames are expressed, and how they shift during discourse, leads to the next construct – a **discursive transaction** [1] (Fig. 1), defined as a sequence of steps in a political conversation that begins with reading or hearing an incoming message, followed by assessing the contents of that message and generating cognitive and affective responses. The final step of the discursive transaction is the reply. In epistemic graph practice, the reply phase of a discursive transaction is a codable utterance.

A **response grammar** refers to everything in a discursive transaction except the initial message or communication [1]. It thus includes **cognitive appraisal** of incoming messaging, emotional reaction to it, and reply (if any). Response grammars were originally referred to as emotional grammars [1], in recognition of a perceived underemphasis of the role that emotions play in the generation and analysis of polarized political discourse. Mathematically, a response grammar can be seen as a template based on probabilistic and acculturated norms that predict how an individual responds following an incoming communication in a conversation. A response grammar answers the question, "What is the most likely response, shaped by emotion, that might be expected to follow from a given input or provocation?" The response grammar for a compliment might involve a simple thanks. In contrast, the grammar for an insult might involve a retaliatory insult, anger, or alienation. Earlier papers [10] have enumerated relatively simple grammars or patterns of responses as they might appear in social media threads. The simplest (and most predictable) examples involve thanking someone for a compliment or responding with hostility to a directly offensive comment or insult.

But grammars more typically assume many (often competing) layers of complexity. For example, Table 1 furnishes a sample scenario with more layers than responding to a simple compliment or insult. It is referenced later in the description of the three modeling tools. For discussion purposes here, response grammars manage current relevant emotional factors, including those that relate to an individual's own perceived vulnerabilities. In the Table 1 scenario, several affective strata or factors contribute to the whole. One factor may be guilt (and fear of being exposed in an unfavorable light): X knows that Y is at least partially right. This realization may add anti-social incentive to belittle or to delegitimize Y to minimize the effect of the attack - Y has become an identity threat to X for telling the truth as Y sees it, and in a way that might plausibly garner voters' attention, to the detriment of X. Another potential emotional layer is quite different: X takes true and heart-felt satisfaction in the social good that the extra spending will produce. And X also enjoys *selfish* satisfaction in believing that the vote will help keep her or him in office. The active response grammar must manage multiple, affectively intense and sharply contrasting layers, some of which (as in this example) are attached to guilt, animus, humane benevolence, and self-interest – an unsurprising mix of both prosocial and antisocial factors. In whatever way Y then replies, the exchange has amplified the acrimony between them, as well as between their respective followers. The resulting epistemic frames shifted, perhaps only slightly, but now they incorporate the emotionally charged exchange and the polarizing feelings the exchange engendered.

The underlying public policy issue – i.e., whether the value of the spending merits passing the bill – has legitimate tradeoffs that constitute the critical public policy issues, but the tradeoffs never seem to get evaluated properly. Instead, they come shrouded in antagonistic charges and exchanges that result in hard feelings, anger, and unwillingness to treat an opposition's voice as valid. If legitimate public policy discussion represents "signal," the signal to noise ratio in this example might rhetorically be as little as 10%, and even that 10% is contaminated by the ill-will of the 90% noise. In this scenario, any next step that includes distortions, misinformation, or disinformation in the exchanges is critically important. When an individual perceives themselves falsely attacked in any context of consequence, the individual is likely to experience outrage and will retaliate with whatever tools might be available. An accusation perceived to be false is one of a handful of message categories that provoke high valence negative emotions such as intense outrage or fear in the response grammar, dual emotions that can then be propagated back into the discussion, or left to simmer, or both. In the realm of social media, this can include increased acrimony, sarcasm, or discord – and a natural polarization and delegitimizing of the other party. When these emotionally-charged messages go back into the discourse, they activate new response grammars with intense, similarly negative, emotional valence.

Fig. 1. Five phases of a Discursive Transaction. A primary thesis of this framework is that emotion exaggeration and cognitive deprivation in Phases 3–4 lead to dysfunctional discourse. The Response Grammar involves the final four phases.

What is the merit in breaking down an imaginary political exchange – the kind that can take place regularly over social media -- and how is it relevant to QE research methods? The intent in decomposing this fictitious exchange and fitting it with terms such as epistemic frames, discursive transactions, response grammars, and high-valence activations is to create a language of investigation that lends itself to political discourse models that can help to clarify the pathologies of dysfunction.

The ascent of social media has complicated those pathologies. It has significantly intensified the flow and variety of polarizing inputs which perpetuate simmering anger, disgust, and other emotion-rich responses, especially responses with high-valence outrage activations. This arises from several factors. For example, contemporary social media trigger still poorly understood physiological mechanisms of screen fascination and addiction [11]. Compounding the effect of those mechanisms, humans have evolved a retaliatory instinct that makes it difficult to step away from perceived aggression, antagonisms, or insults levelled by others; this retaliation trait, often fueled by anonymity, readily plays into cultivating fomenting discord on social media screens. Furthermore, as noted earlier, monetized algorithms and public figures alike intrinsically intensify parallax by fragmenting and distorting information flows [8]. The algorithms incite new polarizing angers and resentment because doing so increases clicks, readership and revenue [7]. The polarization feeds itself and expands with highly enmeshed pathologies.

2 Three Modeling Tools

Applying discourse modeling tools such as those below to help make these complex pathologies more visible will not undo the pathologies. Such models, though, can contribute to a kind of **explanatory relief** that validates rancor and the collective distortion it induces but also supplies alternative, prosocial, and accurate ways to make sense of the intransigence we see in one another. Even explanatory relief is not a sufficient condition for undoing the pathologies either, but is a necessary one and it is foundational for moving beyond a season of angry and injurious stalemate.

2.1 Modeling Tool 1: Epistemic Network Analysis, with Extension

Earlier papers have proposed and demonstrated the application of epistemic network analysis (ENA) for investigating limited forms of socially-mediated political discourse [1, 2]. The formulation of a codebook for political discourse included worked examples that modeled selected political commentary threads in online US newspapers between 2020 and 2022. These models showed patterns of both (a) acrimonious and civil discourse in political commentary, and (b) ENA subtraction models to depict differences between threads. The papers also introduced earlier versions of the constructs (e.g., epistemic frames and response grammars) appearing in the paper's previous section.

Discussions included in these earlier papers contributed to interpretive loops around dysfunctional discourse, and building arguments that contemporary political discourse in social media shows minimal evidence of intellectual humility (defined as the willingness to change one's mind when confronted with new information or perspectives). In the language of ENA, intellectual humility denotes a willingness, or capacity to shift one's epistemic frame upon encountering affectively or epistemically persuasive factors that support such shifting. Misunderstanding both the importance of and the value of intellectual humility may prove one of the most influential variables in developing dysfunctional discourse repairs.

The previous papers also suggested that a fundamental epistemic fallacy is often at play in political discourse, the fallacy that two apparently contradictory interpretations of events cannot be valid simultaneously. In reality, perceived opposites can simultaneously have validity for many reasons, but the flawed logic, especially in social media threads, incorrectly concludes that a position contrary to that held by an individual must be untrue and subscribers to it are thus intellectually inferior or morally defective.

Acting upon an epistemically flawed premise that someone who holds a different point of view is intellectually deficient or morally defective mistakenly invites and incites indignation and scorn, further escalating polarization. It prevents productive discourse that actually explores, compares, and contrasts the factors that can lead to different conclusions, and thus potential evolution of our collective thinking.

Constructive, collective discourse is marked by productive problem-solving, social trust, and collaborative satisfaction. The reductive logic outlined in the previous paragraph primarily produces alienation, ill-will, and mistrust, all of which then become recycled into the next round of discursive transactions. Earlier work [1] examining discursive transactions highlighted not only a lack of intellectual humility, but a related, and even more pronounced lack of gratitude for the respective contributions of those from other political perspectives. The ambient implication of any conversational context involving political discussions devoid of gratitude is that those of differing perspectives merit no more than civility, if that, and that their discursive inputs do not contribute to societal well-being. Yet mutual gratitude, when authentic, is one of the most powerful adhesives in social trust formation [12], or in the well-being of family units [13]. ENA graphs that map hostile discourse did not only find a lack of connections involving gratitude for those of differing political perspectives, they simply found *no* instances of gratitude at all.

Table 2. Coding for Four Sample Utterances

Construct	A	B	C	Number of segments the utterance produces
Utterance 1	1	1	0	One (AB)
Utterance 2	1	0	1	One (AC)
Utterance 3	0	1	1	One (BC)
Utterance 4	1	1	1	Three (AB, AC, BC)

Despite the strength of these findings, using ENA to model epistemic frames and socially-mediated political discourse has limitations. One of the most notable is the relatively small number of variables that can realistically fit into an ENA graph [14]. This limitation is inherent to any model visualization, and to the mathematics of variable decomposition that are foundational to representing complex discursive phenomena (such as political epistemic frames and socially-mediated political discourse). The proposed modeling tools of CAS theory and ANNs in the following sections present compelling tradeoffs. While they do not produce the ENA's powerful visual models, they may effectively reflect other informative system dynamics across myriad variables.

The use of CAS theory and ANNs may also enhance modeling of one aspect to which ENA has already made a signal contribution to quantitative ethnographies: *relationships between constructs.* Among ENA's most compelling affordances is visualization of the intensity of relationships between construct nodes. ENA not only depicts the existence of a connection, but its intensity by way of edge saturation. Yet one seemingly inherent limitation is that ENA network graphs only depict *dyadic* connections – edges, by definition, only appear between two constructs. Interpretations must rely on a holistic view of the aggregate structure of all visualized connections between constructs, but the dyadic nature of each edge can obscure possible important information in the following way: each utterance can be considered an n-tuple of 0s and 1s, where n is the number of constructs coded for the graph. The graph can depict the existence of ordered pairs of activated constructs (i.e., coded with a 1) embedded in the n-tuple. The ENA graph only depicts coded pairs, because edges connect only two points.

This means, for example, that connections between three constructs A, B, and C, can (a) appear separately in three utterances, or (b) appear in as few as a single utterance. Depending on segmentation, Utterances 1–3 in Table 2 will yield the same graph as Utterance 4. All four utterances in the same segment yield the same connections as Utterances 1–3 repeated, i.e., constituting double edge saturation. Yet Utterances 1–3 have a story that could differ substantially from the story behind Utterance 4, with no difference in the visual model. This could be relevant in multiple disciplines in which dyadic occurrences differ sharply from triadic (or quartic) occurrences. One practical path to distinguish AB, AC, BC combinations from ABC combinations is the use of color coding for the triads or higher order n-tuples. If color is not available, visual offsets (such as Fig. 1) are also possible.

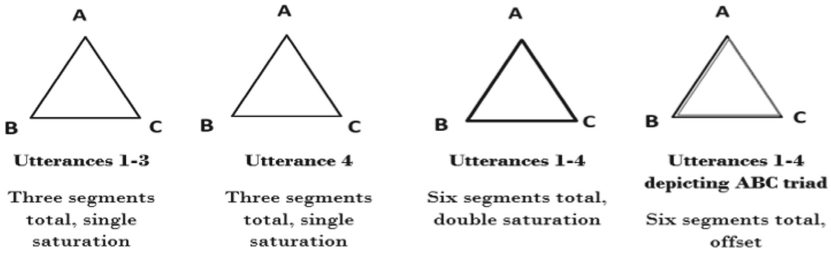

Fig. 2. Mapping Utterances from Table 1

What value might color-coding or visual offsets (such as the last triangle in Fig. 2) specific to 3-tuples (or n-tuples more generally) provide? Such techniques could identify the presence and intensity of co-occurrences of three or more constructs, and, similarly the absence of such combinations. Another possibility is to treat 3-tuples as connecting a set of nodes different from 2-tuples or ordered pairs (e.g., construct A is graphed as construct A′ if it appears in a 3-tuple or higher-level vector. Modifications of this type may extend the model's theoretical purchase in situations where ethnographies highlight not only co-occurrence of constructs, but distinctions in how the co-occurrences combine to change interpretations (e.g., where triadic or quartic connections require different interpretations than dyadic connections).

2.2 Modeling Tool 2: Complex Adaptive Systems (CAS) Theory

The second modeling tool involves complex adaptive systems (CAS) theory [15–17] as a means to analyze socially-mediated political discourse [18]. The theory and metaphors of CAS may provide a unique lens for understanding layers of dysfunctional discourse, and the self-propagating, downward spiral that dysfunctionality may induce. As the example in the Table 1 response grammar suggests, dysfunctional political discourse can be shaped less by the civic or social topics that are the focus of conversation, and more saliently by the social mediation of the conversation. To vary Marshall McLuhan's aphorism, the message becomes far less important than the medium.

In theory, and now quite likely in practice, social mediation of political conversation can become more prominent or salient than the putative topics of those conversations. The topics recede in importance or simply serve to seed escalating polarization before vanishing into the ensuing discordant communication. Giving the conversation and its rancor or other dynamics a higher priority than the underlying issues produces a reversal that not only obscures and prevents meaningful debate about central issues, but which currently seems structurally guaranteed to worsen if left unchecked. This reversal spawns in political conversation a matrix of natural signal suppression (a tendency to understate my weaknesses and my opponent's strengths) and amplification (a tendency to overstate my strengths and my opponent's weaknesses). It also can create opportunities for misrepresentation, misinformation, and outright disinformation.

This paper proposes to interpret political discourse as a CAS with certain definable and testable properties that can expose latent patterns that fuel dysfunction and therefore, merit broader recognition and scrutiny. The discussion positions classical CAS constructs (appearing in bold face below) in a discourse context in the following way: a **heterogenous population of autonomous agents** (individuals and political groups) in **dynamic, if intermittent engagement with one another** (in this context, through social media) in an **ecosystem defined by limited rule sets for agents' interaction** (including response grammars defined by individual epistemic frames, along with communication procedures defined by the medium), **feedback loops** (such as comment threads in social media and political developments and **self-modification of the overall system alongside discontinuous transitions** (e.g., new polarization, narratives, elections, or political events).

Every discursive transaction – that is, every instance of an incoming message, the cognitive appraisal and emotional reaction to it, and the response or feedback to it that ensues – modifies the complex system. Each discursive transaction encounters and modifies individual epistemic frames, and then introduces new feedback or encounters new responses into the complex system. These combine with responses that other individuals (agents) in the complex system then process through their own epistemic frames and response grammars, each in turn adding to the activity and polarizing evolution of the system. Using the constructs of response grammars, epistemic frames, and discursive transactions, a CAS interpretation may enable a realistic, microgenetic focus on the mechanics of polarization, and its ensuing escalation. CAS may incorporate emotion and cognitive appraisal theory as paramount tools for explaining dysfunctional patterns and examining how individuals contribute to increasing polarization, especially in accusatory or hostile discourse. A suggested explanation for the CAS interpretation employs the type of parallax of discerning an object in one location suggested by light refractions, when it is actually located elsewhere – as a metaphor to explain that both emotion and cognition are implicated in the misreading of and the responding to political discourse cues. The parallax mechanism distorts feedback loops in the complex system that continually escalate acrimonious dysfunction.

The paper argues that the cumulative effect of parallax-impaired feedback loops not only damages political conversation, but degrades it into a melee where each side (for example, left versus right) holds and expresses conviction that the other side poses obvious, existential risks to the nation. CAS theory helps explain why such convictions can become self-fulfilling: adaptive systems adjust and modify agents (humans and political factions) within the system in such a way as to make them more aligned with the system. The system's tendency toward conformity then causes people to trend into divergent polarities that (a) intensify misrepresentation, (b) create layers of misunderstanding, and (c) attenuate any ability to summon the collective wisdom required to face national shortcomings and crises. Finally, a CAS interpretation seeks to organize the nuanced, myriad factors inherent to political discourse into a novel, constructive, and holistic paradigm.

2.3 Modeling Tool 3: Artificial Neural Networks (ANNs)

Artificial neural networks (ANNs) mimic biological neural activity in ways that traditionally have helped to design pattern recognition systems and predictive algorithms [19]. They form the building blocks of the large language modeling (LLM) behind generative transformer model chat bots and future artificial general intelligence (AGI).

In contrast, the quite modest potential of ANNs in this paper's context involves modeling political discourse by conceptualizing an epistemic frame as a neural network, a network that can be represented with hundreds or thousands of nodes, each of which has a different weight and contribution to the other nodes, and to the overall epistemic frame. Components of the conceptualized epistemic frame can include: moral or ethical commitments, the enduring psychological effect of memorable experiences, acculturations, perceptions about political movements, knowledge (both accurate and inaccurate) about history and contemporary events, perspectives (wise or otherwise), and both emotional and cognitive dispositions. Each of these contributes to an overall, dynamic, epistemic frame that shifts, either slightly or substantially, with every discursive transaction, and with assimilation of new information that interactions with others entail.

Elements of a political perspective, or epistemic frame, are not intrinsically rational, or easy to describe. Financial or reputational self-interest, the ubiquitous human propensity to exert control over others, and threats to one's sense of identity, all contribute to an epistemic frame. ENA can model a relatively small number of nodes in an epistemic frame, with the general understanding that any single node can have a relationship with each of the other nodes. Use of neural networks to model epistemic frames maintains the same expectation, i.e., that each node (or neuron) might have a connection to every other neuron. The neural network interpretation can be tested with computer simulations that are theoretically more scalable than that of ENA simulations. The ENA graphing tool has the constraint of converting the model to a two-dimensional visual representation of nodes and edges. ANN modeling, however, accommodates thousands of neurons, or nodes, that connect with one another without requiring computational decomposition.

The value that might arise from informally cataloging the components that contribute to a political epistemic frame, and then treating them as heterogenous nodes (or neurons) in an artificial neural network model, is as follows. First, each node has a differential weighting, or prominence, in the frame. This feature of neural network theory corresponds to the universal tendency for political viewpoints to give higher prominence or priority to some issues over others. Theoretically, weightings may include cognitive or socio-affective commitments or dispositions, including variables associated with personal identity or security. Second, the nodes are interconnected, and can affect or shape one another. Third, the "learning" process associated with artificial neural network models entails multiple processing layers, yielding a new set of weights on each node, new weights that take form through processing response grammars and that result in a new epistemic frame.

In this interpretation, the epistemic frame constitutes the input architecture of a neural network model; a discursive transaction, operating under the rules of the response grammars, represents the learning or processing layers; the modified epistemic frame with different weightings for each of its nodes of neurons is the output. Note that the modified epistemic frame is only one result of the discursive transaction. A second, principal result is the actual response that the processing produces as the epistemic frame assimilates the message, and responds to it (i.e., the final phase of the discursive transaction in Fig. 1). That message then can activate new discursive transactions – i.e., the discourse or conversation continues (Fig. 3).

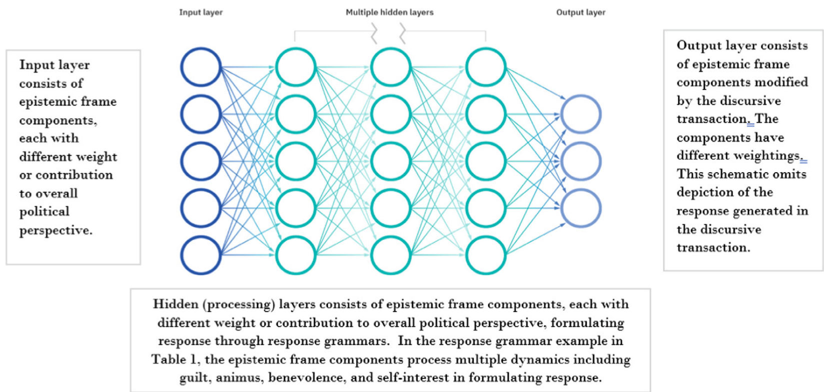

Fig. 3. Epistemic Frame Modification During Discursive Transaction – A Neural Network Interpretation image source: ibm.com/blog/ai-vs-machine-learning-vs-deep-learning-vs-neural-networks/

Discursive transactions that entail high-valence activations (such as those receiving false, but anger or rage-inducing accusations, reports of injustice or betrayal, or ominous news) can provoke learning layers that produce new weightings. New weightings that result from discourse with high-valence activations will likely result in new weightings with significantly stronger negative emotion towards and polarization away from the individuals and views that started the initial transactions. The re-weighted epistemic frame generates new messages that reflect – and induce – greater polarization.

Such a dynamic of self-fueling escalation of negative affect is at least one possible result of a neural network modeling approach. Testing such an approach initially would require analyzing sufficient data, both to structure an epistemic frame representation and to generate weightings for its nodes. The approach would need to detect shifts that discursive transactions, especially those with high-valence activations, would induce, followed by detection of the propagation shifts. Testing such a model empirically would likely prove prohibitive, but simulations could prove viable, with the goal of depicting whether the network produces inflection points, beyond which possible steps towards comity, compromise, gratitude towards others with differing views, or collaboration, become increasingly rare. Visual representation of those dynamics could depict the conjectured pathology of negative interactions that in turn feed increasingly negative interactions. Mapping this pathology is a critical aim of the modeling endeavor.

2.4 Why Building Blocks for a Science of Dysfunctional Political Discourse?

This paper relies heavily on the constructs of epistemic frames and response grammars to build a case for suggesting three tools to model dysfunctional political discourse.

The paper a) affirms the viability of ENA as a tool for modeling dysfunctional political discourse and suggests a dimensional enhancement (coloring selected n-tuples for n > 2) to display connections between nodes; b) maps ways that political discourse can be represented as a complex adaptive system (CAS); and c) suggests that neural networks can model microgenetic shifts in individual components and the total structure of an epistemic frame. Political discourse literature has already employed several quantitative modeling approaches [e.g., 4, 5], but none involve conceptual tools of epistemic frames or rule sets for political conversation. Epistemic frames and rule sets, however, are tools that lend themselves to (and require) a different level of theoretical traction. In doing so, they likely contribute to making the pathologies of dysfunctional discourse more visible. The epistemic frame construct represents a holistic network of myriad factors that comprise a political point of view. A response grammar identifies likely short-term ways that a political conversation shapes and is shaped by an epistemic frame. Each of the three proposed tools suggested in the paper offers different emphases for modeling these constructs, with the latter two of CAS and ANNs potentially able to model how discourse, with its dysfunctionalities unabated, can eventually become a self-fueling polarization spiral. Table 3 summarizes each of the three approaches in terms of affordances and tradeoffs, including reference to the critical role of response grammars in each.

2.5 Comparing and Contrasting the Three Tools: Summary Notes

Quantitative ethnography is often associated with the epistemic network graphing tool that co-evolved with the QE research community. While CAS and ANN do not seem to appear as modeling approaches in the QE literature, this paper suggests that they belong alongside ENA as a means to decompose a phenomenon quantitatively in order to augment our understanding of it. This paper suggests that the umbrella of quantitative ethnography should encompass what might be considered computational modeling, computational ethnography, or the application of more mathematized thinking, computational thinking, algorithms, and simulations of political discourse.

Terms such as quantitative ethnography reflect a powerful development in both academia and society more broadly, the realization that the constructs we apply to enable efficient organization of knowledge disciplines– chemistry, history, psychology, mathematics, etc. – may have great value in helping to generate knowledge, build universities, or make sense of the world. They are also inherently limiting, in the sense that there are few, if any, phenomena that do not reflect many disciplines. Terms such as multidisciplinary, interdisciplinary, or transdisciplinary reflect striving to decouple the knowledge-generating enterprise of understanding the world from the artificial boundaries of different disciplines [20] that have been an important conceptual device in building knowledge, but that are becoming increasingly outdated. Each modeling tool this paper relies on building blocks that are inherently heterogenous and consistent with interdisciplinary or transdisciplinary perspectives, including modeling that encompasses affective factors in addition to those traditionally referred to as epistemic.

Final Notes

The terminology of dysfunctional political discourse may tacitly convey the idea that political discourse has been functional, or at the very least less dysfunctional, in the

Table 3. Contrasting Three Tools for Modeling Dysfunctional Political Discourse

QE Tools →	Epistemic Network Analysis	Complex Adaptive Systems	Artificial Neural Networks
Description	• ENA models an individual's political perspective as an epistemic frame, emphasizing static or snapshot views of frames as ENA graphs.	• Political discourse is a definable, self-modifying CAS with properties not inherently related to underlying policy issues.	• "Learning" is a dynamic process of epistemic frame evolution through changing weightings on each node in the network.
Affordances	• Most straightforward tool for modeling empirical data. The underlying epistemic frame theory is applicable across all three tools. • Subtraction modeling highlights changes within individual or differences between groups.	• CAS approach partitions or separates discourse from the underlying issues that are the subject of discourse. • The self-modifying nature of CAS provides explanatory power for **collective** deterioration of discourse.	• Self-modifying nature of neural networks provides explanatory power for deterioration of discourse by **individual**. • Visual model depicts components of epistemic frame with weightings to emphasize components differentially.
Tradeoffs	• Difficult to model dynamic constructs such as discursive transactions. • Smaller number of nodes.	• Simulations are theoretically possible but visual CAS depictions are difficult.	• Difficult to model large number of nodes (epistemic frame elements) empirically.
Role of response grammars	• Furnish a probability rule-base for discourse that ENA models.	• Furnish a rule-base for system agents that can define simulations.	• Describes hidden layer interactions and activations of classical ANN theory.

past. This paper makes no such claim. Digital social media has helped produce and advance a chapter of global reckoning for profound systemic injustice and structural oppression. This represents immeasurable benefit to global society. But, like the worn comparison to the value and hazards faced upon the prehistoric discovery of fire, we again face tradeoffs – and those brought with the advent of social media are of extraordinary dimension.

It is almost impossible to imagine the benefits social media have brought, and are still likely to bring, to governance and its underlying political speech. It is, likewise, almost impossible to imagine the intense harm to humanity that social media can foster and inflict.

If the above comparison is apt, i.e., that extreme benefits and extreme hazards are possible, the solution path does not likely lie in reliance solely upon government or corporate shareholder regulatory mechanisms, but rather in building new practices and norms within the media realm. New practices and norms are not likely to reward any particular side in any political category, but that outcome, in itself, is not predictable. An overarching premise of this effort is that our forms of communication have so distorted not only our *perceptions* of others, but have distorted us as humans, both collectively and as individuals. In an improved realm where alienating communication, reactions, escalation, and mutual disgust give way to more salubrious, and attainable practices, how we view ourselves, and others, may no longer so closely resemble the fault lines and tribalism that define our contemporary political discourse. The aim of this paper is thus not ultimately simply to encourage civil conversation, nor to encourage compromise, nor to encourage more persuasive advocacy of perspectives. Its intention instead is to use discourse analysis to raise awareness that the present conditions of conversation are all wrong. We are at a point in history where the conditions of political conversation are severely damaging society collectively and its members individually, with social media acting as a rapid accelerant and key factor in that process. The paper thus seeks to contribute to conditions for resetting conditions of political conversation. That endeavor is neither as optional nor impossible as might be thought.

The modeling tools proposed in this paper, clarified and at full strength, may provide explanatory relief for why the polemics, advocacies, rhetoric, rage, and vilifications that fill our political web pages and that seem to tickle or please the like-minded are oddly ineffective in convincing or neutralizing others – and seem, instead, to intensify their resistance. The modeling tools are meant to clarify this pathology and to open up the idea that we have no idea of how much more effectively we would operationalize our moral commitments and perceive or interact with one another if the conditions of conversation were not so contaminated.

Initiatives are underway globally that seek to grapple with and change the conditions of conversation [7]. They are beyond the scope of this paper, and are of different flavors, methodologies, and political frameworks. They merit exploration and opportunities to flourish as the need to alter the dynamics of political discourse becomes recognized not as optional endeavor but as an existential requirement for maintaining free and fair democratic institutions and to recover from damage that has already been inflicted on them. That is an "emotional reset" [21] path that will ultimately entail shifts in the zeitgeist of political discourse in social media. Whether that reset occurs slowly or rapidly, peacefully or otherwise, is yet to be determined. The modeling tools proposed here, however, may help make clear that the current path is almost mathematically guaranteed to worsen until such a reset takes place.

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