Deliberation as an Epistemic Network: A Method for Analyzing Discussion

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Abstract. Deliberations are discussions about what an institution, community, or nation should do, and are essential for maintaining a robust democracy. This study examined whether Epistemic Network Analysis (ENA) can complement existing methods for assessing deliberations, none of which fully account for the dynamic interplay among specific speech acts and speakers that unfolds over the course of a conversation. In this pilot study, students at two universities deliberated about the same issue online. ENA models of discussions at each university with the content of speech acts as nodes showed differences between discussions at the two universities that were consistent with a qualitative analysis of the transcripts, but also revealed patterns that were not initially apparent in the qualitative account. This suggests that ENA is a valuable tool for modeling deliberations.

Keywords: Deliberation · Epistemic Network Analysis · ENA · Habermas · Democracy · Deliberative democracy

1 Introduction

Deliberations are discussions about what an institution, community, or nation should do. Deliberation is important in a democracy. It allows individuals to influence public opinion and official decisions and may convert opinions and desires into more reflective judgments. Deliberation is a subset of conversation that meets certain normative criteria, such as reasonableness and equity, although these criteria are debated.

Analyzing deliberations can yield insights that inform efforts to change the format and structure of conversations or to educate people (participants and moderators) to play their roles better. It can also inform people who need to decide whether a given discussion met a standard for being a deliberation. Although judgments of quality ultimately depend on normative principles, rigorous mathematical methods for analyzing and representing deliberations can provide the material for debating such principles and applying them to specific cases.

One general approach to analyzing a deliberation is to treat the ideas that individuals convey as network nodes, and the connections they cite or imply between their own ideas as links. Then it is possible to model each participant's statements during a deliberation as an epistemic network (a network of ideas), and the discussion as a

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whole as one amalgamated network for the group. This method benefits from the special affordances of Epistemic Network Analysis (ENA), which produces a network visualization where the positions of nodes are meaningful and comparable across separate discussions.

In this study, two demographically different groups of students at different universities discussed the same topic (the social determinants of health) in online fora. They answered survey questions about their impressions of the discussion, e.g., how diverse they considered the opinions they heard expressed. The text of their discussions was analyzed using ENA. Ideas were coded, and ideas that were expressed in close proximity were considered linked by the speaker. Graphs were generated for the separate discussions and were compared. The resulting models of the two discussions confirmed the authors' impressions but also provided clear and quantified representations that would be useful for assessment.

2 Theory

Deliberation is a means to improve opinions by giving citizens the benefit of other people's perspectives. President Woodrow Wilson said that "The whole purpose of democracy is that we may hold counsel with one another" [44]; and some contemporary political theorists share that view [1].

According to the influential theory of Jürgen Habermas, deliberating citizens exchange reasons for why their claims about public issues are: (1) true, (2) just or fair, and (3) sincere [18, 19]. A *valid communication* is one that would persuade other people of its truth, justice, and sincerity in the absence of coercion and other barriers, such as lack of time and attention. A *valid claim* would attain consensus in what Habermas envisions as an "ideal speech situation" in which "no force except that of the better argument is exercised" [17]. For instance, a speaker's popularity or status would not matter; only her ideas would. The benefits of seeking consensus include better public understanding of what is right and good and richer and more defensible inner thoughts [18].

Habermas has contributed to the theory of *deliberative democracy*, in which citizens' voluntary conversations about current, controversial issues in the public sphere play a politically essential role [9]. Many others have enriched the theory or sought to apply it by designing deliberative fora or reforming laws and policies to encourage deliberation. Deliberating about current, controversial, public issues is also a valuable educational experience, enhancing students' knowledge of the issues under consideration, grasp of alternative perspectives, skills for interacting with other people, and motivations to participate in civic life [23, 39].

In real life, conversations can go well or badly. Habermas is fully aware that the "*ideal* speech situation" is a heuristic; actual discussions never meet the ideal. For example, discussions of contested political issues in the United States frequently display such flaws as *motivated reasoning* (selecting evidence to confirm a pre-existing view), *balkanization* into like-minded groups, *incivility* that discourages people from participating, and the *dominance of ideology* over evidence [16, 25].

Thus, the problem of assessing *deliberative quality* arises. The raw material for assessment may be a transcript of an actual conversation. On its face, it shows a whole series of utterances attributed to various people that can be coded in various ways, e.g., as right or wrong, civil or uncivil, a question or a claim. Deliberation, however, is more than just a temporal series of statements, because (in Habermas' terms) deciding whether a given turn of talk is a valid communication or valid claim can only be determined by the larger context in which it sits. Characterizing the quality of a deliberative discussion thus requires accounting both for the individual statements of participants *and* the way in which they relate to the statements of others in the conversation. Only with such a contextual model could we characterize statements as being *deliberatively virtuous*, and therefore only with such a model could we apply normative judgements about the degree to which deliberative ideals were met in a discussion.

We argue that creating such a model would be an important step in both the study and practice of deliberation because being able to make such assessments should yield insights into how to improve actual discussions in educational settings and civil society alike. Specifically, we advocate the application of ENA to the assessment of deliberation. ENA is a well-developed and widely employed method, but it has not previously been applied to deliberations of public issues. We show that it can address limitations in existing methods for assessing deliberative quality and improving deliberations.

2.1 Current Approaches to Evaluating Deliberation

Many efforts to assess deliberations rely on coding transcripts for evidence of deliberative virtues, such as hearing another person's arguments, or vices, such as expressing disrespect [14, 41]. Other approaches survey participants and/or independent observers for their general impressions of the quality of an observed deliberation [27].

To address the subjectivity of evaluations by human observers, many studies use rubrics or scoring guides. Multiple raters apply the same rubric to the text of a deliberation and resolve disagreements. A prominent example is the Deliberative Quality Index (DQI) [41]. An alternative approach, meant to address concerns about raters' subjectiveness, is to count specific deliberative "moves" and then compare the frequency of such moves across multiple discussions [3, 20, 22, 28, 31, 43, 46].

Such methods have produced insights about where and when deliberation occurs and who participates. However, we see limitations that can be addressed by new methods that employ network analysis—and specifically, ENA.

Any method that asks human raters to assess speech must direct their attention to some specific, concrete material. For example, raters can be asked to evaluate a whole deliberation according to a rubric or to assess each individual's participation. In DQI, "The unit of analysis… is a speech, that is, the public discourse by a particular individual delivered at a particular point in a debate. Thus, the entire discourse is broken down into smaller speech units" [41].

Choosing a focus for assessment is challenging because a deliberation consists of many utterances by at least several people, unfolding over time and relating to each other. For instance, a given speech may be a response to something someone else said. Bächtiger and Parkinson advocate paying attention to the "interpersonal dynamics"

[5] in deliberation. But it is unlikely that human raters can rigorously assess the relationships among all the “smaller speech units” and all the speakers and listeners in a conversation, because these are very numerous. One approach to constructing more contextual models has been to use *network models* that account for the relationships between people and ideas in a discussion. For example, Black and colleagues [4] use network analysis in which the nodes of a network are people and the links between them are different forms of discourse, such as agreements, disagreements, or questions. They argue that a network visualization enables the “discovery of patterns and relationships in data that would otherwise be obscured.”

In this paper, we build on this network analytic approach. Like Black and colleagues, we propose that network analysis will reveal features of a discussion that have face validity and normative or evaluative significance and that would otherwise be overlooked.

2.2 Networks in Deliberation

People who discuss a social or political issue can be understood as members of a *social* network, in which the nodes are individual human beings, and each link represents one person influencing another. Social networks can be modeled by looking at actual patterns of interaction between individuals. For example, if Participant 2 (P2) in a discussion is consistently replying to or referencing the comments of Participant 1 (P1), but P1 rarely refers to P2, then we might assert that P2’s thinking is influenced by P1 more than P1’s thinking is influenced by P2. Social network analysis is not a focus of this paper.

Each individual’s views on the issue under discussion can also be conceptualized as an *epistemic* network: a set of linked ideas, where the nodes are ideas being discussed and each link represents an individual’s belief that the ideas are related to one another. As individuals discuss a topic, they disclose some of their own ideas and connections, and these in turn connect with others’ points. For example, if Participant 1 (P1) in a discussion of climate change argues that we should *limit carbon emissions* because *human activity contributes to climate change*, then they are making a claim that two ideas (carbon emissions and the contribution of human activity to climate change) are related to one another. If Participant 2 (P2) replies by arguing that any actions we take towards *mitigating climate change* need to be *equitable to populations with fewer resources*, then they are also linking two ideas (mitigation and equity). However, by making this statement in response to P1, P2 is also linking both mitigation and equity to carbon emissions and to human activity as a driver of climate change [37].

These accumulating statements can be modeled as an epistemic network for the group, or as a set of epistemic networks for each individual, and these networks can be visualized either as evolving structures or as a representation of the discussion as a whole. Diagramming discussions as epistemic networks reveals areas of focus (what is being connected to what) and degrees and types of complexity (how many connections there are and how strong are they).

As the epistemic network of the group grows and changes, both individuals’ opinions and their locations in the social network may change. Both the social network and the epistemic network can be characterized holistically, not just as the aggregate of distinct utterances.

2.3 Epistemic Network

Epistemic networks can be modeled using *epistemic network analysis* (ENA). ENA models the structure of connections between ideas (referred to here as nodes or Codes) both within and between individuals.

ENA assumes: (1) that it is possible to systematically identify a set of meaningful features in the data (Codes); (2) that the data has local structure (conversations); and (3) that an important feature of the data is the way that Codes are connected to one another within conversations [37, 38]. For example, the Codes in a deliberation about climate change would be the key ideas or issues of climate change. That is, a main theoretical assumption of ENA is that repeated co-occurrences of two or more Codes in the same portion of a discourse can reveal epistemic networks which characterize an underlying Discourse, or pattern of talk within some cultural context [15, 37]. ENA models the connections between Codes by quantifying the co-occurrence of Codes within conversations, producing a weighted network of co-occurrences [29].

In the discussion of climate change described above, the hypothetical speaker P1 could link two ideas with a logical connector—for example, "*Because* human beings are causing global warming, we had better limit carbon." However, ENA does not rely on such explicit connections. It is based on theories of discourse (more specifically *discourse analysis* and *epistemic frame theory*) in which temporal proximity entails semantic linkage. That is, because of the nature of human interaction in typical settings (including but not limited to deliberative discussions), people (a) make internally coherent contributions—or at any rate contributions that reflect the structure of their ideas—and (b) respond to the context in which their utterances are made. Thus, temporal proximity of concepts implies meaningful relationships. There are, of course, specific instances where one or the other of these assumptions might be violated, and any mathematical analysis is only a model of some phenomenon in the world. However, our detailed examination did not suggest any reason to believe that these assumptions were violated either frequently or systematically in the data used for this study. It is true that the version of ENA used here does not model the valence or causal claims being made between ideas, and this is a topic we return to in the discussion. For more on these issues in general, see [37].

In ENA network visualizations, the positions of nodes are fixed using a deterministic algorithm (a linear regression) that is (a) performed on the entire set of networks and (b) is co-registered with the ENA metrics that characterize the networks. When integrating a graph produced by ENA, one can attribute *meaning* to the *position* of nodes.

The co-registration of summary statistics and visualizations is made possible by the fact that, in any given ENA space, all networks have the same node locations but differ in their strength of connections, or edge weights. Nodes are positioned such that the centroid of each network (determined by the edge weights) corresponds with the network metric(s) for that network. This co-registration of network visualizations and metrics creates a method for interpreting the dimensions of the ENA metric space.

Networks that score *higher* on a dimension in the network space are those that have stronger connections among and to the *nodes* that are positioned towards the *positive* end of the dimension. Contrariwise, networks that score *lower* on a dimension in the network space are those that have stronger connections among and to the nodes that are positioned towards the *negative* end of the dimension.

As a result, researchers can use ENA to statistically analyze the content (rather than just the structure) of a set of networks, interpret the meaning of those statistics in terms of the content of the networks, and perform visual comparisons of networks. Of particular use in comparing networks is the ability to compare two network models by subtracting their connections weights from each other to create a *difference network graph*. The resulting difference network graph shows which connections are stronger in one network compared to another and is particularly useful for comparing groups of networks (for example, the discussions from two different classrooms) by constructing the mean network for each group and comparing them statistically and visually.

2.4 Research Purpose - Use of Networks in This Study

In this study, online discussions of the same topic in two different contexts were modeled as epistemic networks. Specifically, we use ENA and a Quantitative Ethnographic approach more broadly to address the following research questions:

RQ1: Can ENA be used to measure different deliberative discourse patterns in online forum discussions in similar course from two different universities?

RQ2: If so, what might lead to these differences and what implications could they have on assessing deliberation and developing norms for teaching deliberation?

This method produced substantive findings. For instance, one conversation was more complex (as a whole) than the other, although the less complex one was more consistent with scientific consensus. In general, by applying Epistemic Network Analytics to these deliberations, we clarified and quantified aspects of the conversations that can then be normatively assessed and compared. More generally, in this study we aim to demonstrate how ENA can be used to assess deliberation and inform the development of normative principles for, and principled assessment of deliberative discussions.

3 Methods

3.1 Sample and Settings

Students were recruited from an undergraduate course at Tufts University, a private liberal arts institution in Massachusetts (n = 30), and Kansas State University (KSU), a public institution in Kansas (n = 48).

Tufts students are generally seen as liberal, with few explicit conservatives. KSU is more ideologically diverse. We did not ask participating students about their own ideologies or partisan identities. However, the precinct where Kansas State University is located split 51%-39% for Hilary Clinton over Donald Trump in 2016, and Trump won the neighboring precinct to the west, which contains many apartment buildings catering to KSU students. All the precincts around Tufts University favored Clinton by margins of at least three-to-one, and the nearest precinct that Trump won was a 17-min drive away [6]. Although students can come to either institution from anywhere in the world, these statistics about the two communities offer a meaningful contrast: Tufts is considerably more progressive than KSU.

The Tufts group was racially, ethnically, and culturally diverse (7 students of color and 12 white students; 80% female). However, all of the Tufts students reported that their mothers had completed college, an indicator of relatively high social class. The KSU group was less racially heterogeneous (80% white), and 89% had mothers with college degrees.

Each group conducted three deliberations in online forums, separately from each other. We posit that the epistemic networks of these deliberations changed over time, but on different timescales. Each new discussion has its own epistemic network, which changed every time a student posted a comment. The slate was then cleared for the next discussion. To illustrate an epistemic network, we focus on one specific discussion, regarding the social determinants of health. This discussion was the first of three at KSU and the second of three at Tufts.

In both cases, the instructors (who are not authors of this paper) agreed to ask their students to participate in online discussions, for the purpose of this research study. At Tufts, the course was devoted to science policy. The Tufts students were assigned a substantial reading about the racial and class determinants of health outcomes [8]. They also experienced a class visit by an expert on that topic who emphasized the injustice of health disparities. At KSU, the course was concerned with communication studies. The students received much less direct instruction on the social determinants of health before they discussed that topic online: just a link to a short online document that did not emphasize race or class [33]. Thus, any differences in the discussions might result from the students' demographics, contexts, and prior beliefs or from the way the topic had been presented. We do not purport to explain the differences in terms of causal or contextual factors, but simply to elucidate them.

We also collected social network data by asking students before and after each deliberation to name the other students who influenced them. We interpreted each such response as a social network connection (an edge) from the influencer to the influenced. Counting the number of such connections indicated substantial changes in individuals' network centrality over time that seemed plausibly related to the roles they played in each discussion. However, for reasons of space and because the social network data were simple and preliminary, we do not report those results here.

To measure students' opinions of the topic and their assessment of the deliberation, they were asked before each discussion to write a very short essay describing their opinion of the topic and to answer survey items about their interest in it. After each discussion, they were asked a battery of questions, drawn from [27] about their opinions of the discussion, the issue, and deliberation in general. (Since not all students who participated in this discussion answered all the survey questions, the numbers of respondents vary somewhat in each analysis.)

They conducted their discussions online using a simple threaded comment platform provided for courses at Tufts. At Tufts, the discussions were for credit and graded, and students had the option of a different short writing assignment if they did not want to be part of the research study. At KSU, the discussions were for extra credit, and there was an option of an alternative extra-credit writing assignment for students who did not want to participate in the research. Students who completed all the surveys received $10 gift certificates.

All the text was captured, the speakers were matched with the survey questions, and the dataset was anonymized for analysis.

Two human coders reviewed the text and coded it for the following concepts: Personal Choice, Prejudice, Opportunity, Hard Work, Upbringing, Class, and Race (see Table 1). These codes emerged from a grounded analysis as the main topics of discussion. Coding was validated using social moderation, where two or more raters code the data independently and then resolve any differences to reach consensus on all coding for the entire dataset [21, 37].

Epistemic Network Analysis was then used to analyze the text. Figure 2 shows the results.

We utilized the ENA 1.7.0 Web Tool (version 1.7.0) [29], with individual students as the units of analysis nested within each school. We analyzed each discussion post independently, constructing a network model for each post where a connection between two codes is defined by whether or not they both appear in the post being modeled. The resulting networks were aggregated for posts for each student in the model. In sum, the ENA model was defined as Units: School, Student; Conversation: Post (whole conversation model); Codes: see codebook above.

The ENA model normalized the networks for all students before they were subjected to a dimensional reduction, which accounts for the fact that students had different numbers of posts in the discussions. For the dimensional reduction, we used a *means rotation* followed by a singular value decomposition (SVD). The means rotation produces a first dimension that passes between the mean values of two groups (in this case, KSU and Tufts), and can be read as the dimension which shows the greatest differences between the two groups. The SVD produces a second dimension orthogonal to the first that accounts for the most remaining variance in the data after removing the first (means rotated) dimension. See [37, 42].

Networks were visualized using network graphs where nodes correspond to the codes, and edges reflect the normalized frequency of co-occurrence, or connection, between two codes. The result is two coordinated representations for each unit of analysis: (1) a plotted point, which represents the location of that unit's network in the low-dimensional projected space, and (2) a weighted network graph. The positions of the network graph nodes are fixed, and those positions are determined by an optimization routine that minimizes the difference between each plotted point and the corresponding centroid of its weighted network graph. Because of this *co-registration* of network graphs and projected space, the positions of the network graph nodes—and the connections they define—can be used to interpret the dimensions of the projected space and explain the positions of plotted points in the space. Our model had co-registration correlations of 0.86 (Pearson) and 0.86 (Spearman) for the first dimension and co-registration correlations of 0.81 (Pearson) and 0.79 (Spearman) for the second, suggesting that positions of nodes for the network graphs provide a reliable interpretation of the differences captured on each dimension.

Table 1. Codebook.

Code	Definition	Example
Upbringing	Discussion of raising children including personal experience	Because of how I was raised, I could not truly relate to what my teacher was trying to convey to us
Prejudice/Discrimination	Discussion of judgement or unfair treatment directed against someone or a group of people based on factors including: age, sex, skin color, speech, income, education, sexual orientation, disability, religion and politics	I agree with you... that all races should be treated equally, however this is not the reality of our society. **Discrimination and prejudice** is still very much alive and it definitely affects peoples' well-being
Opportunity	Discussion of situations or occasions which make it possible to have good or bad health outcomes	For some of us, going to college is a thing that we knew is going to happen in our lives and we never question if we might go or no. But for some people they do not have this **opportunity** to afford college…
Class	Discussion of economic/social class (socioeconomic status)	I do believe that race, **class**, and social factors can have an effect on a human being's health and well-being
Race/Ethnicity	Discussion of categories of people who identify with each other based on similarities such as common ancestral, language, social, cultural or national experiences. Discussion of race or ethnicity	For some of us, going to college is a thing that we knew is going to happen in our lives and we never question if we might go or no. But for some people they do not have this **opportunity** to afford college…
Daily decisions	Discussion of making day to day personal choice about how one lives their life	Before I came here, I used to not drink at all, but alter coming here the fact that I was not drinking made me feel like I don't fit into the group. … So again, our friends can influence us in taking **decisions** that could affect our health
Hard work	Discussion or overcoming the odds or difficult circumstances with hard work (classic bootstrap narrative)	Because In my personal experience my mother worked very hard to get where she is today… She worked hard and I 100% believe she has earned and deserves all that she has today

In addition to modeling the deliberations with ENA, we read the deliberations to validate that the network models represented meaningful connections made by students and to identify illustrative qualitative examples.

4 Results

Figure 1 shows the mean discourse network for the social determinants of health deliberation at Tufts (on the left in blue) and the mean discourse network for KSU (on the right in red). Subtracting one network from the other produces the difference network is in the middle.

The graphs on the left (Tufts) and right (KSU) show the mean of students' discourse from each group as a single graph. The nodes are ideas, and they are in the same locations on all three graphs, which allows comparison. As described above in the method section, their locations are determined by a dimensional reduction followed by a linear regression, and as a result, the location of the notes can be used to interpret the axes of the metric space. The links between nodes indicate the relative frequency with which students referred to pairs of ideas in the same post.

The axes can be interpreted by examining the labels of the nodes that are closer to them (similar to principal component analysis). In this case, the positions of the nodes suggest that the left-right axis of the space can be characterized by the contrast between concepts related to personal beliefs (daily decisions and prejudice/discrimination) and concepts related to upbringing, with *personal beliefs to the left* and *upbringing to the right*.[1]

While personal beliefs can be understood as broadly determined by one's upbringing, in the case of this study they have been defined and are expressed differently in the data. Specifically, the code upbringing relates to *direct explicit discussion of raising children or personal childhood experiences of how someone was raised* while, in contrast, the codes daily decisions and prejudice and discrimination refer to *making day to day personal choice about how one lives their life* and *judgement, or unfair treatment directed against someone or a group of people* respectively. In addition these codes cooccur relatively infrequently in the data and are not defining features of the mean discourse network for KSU or Tufts or the differences between them.

The most prominent connection of concepts made by students at Tufts was between class and race/ethnicity. (An example is a Tufts student's statement: "When talking about the Flint, Michigan water crisis, it was shocking to hear that companies … are often built where the majority of the community is minority and low income)." In contrast, the students at KSU made the most connections between class and upbringing,

[1] It is also possible, of course, to interpret the up-down axis; however, we are not making use of that information in this analysis. Because of the dimension reduction technique used, differences between the two groups are projected to the first axis of the metric space, as we will show below.

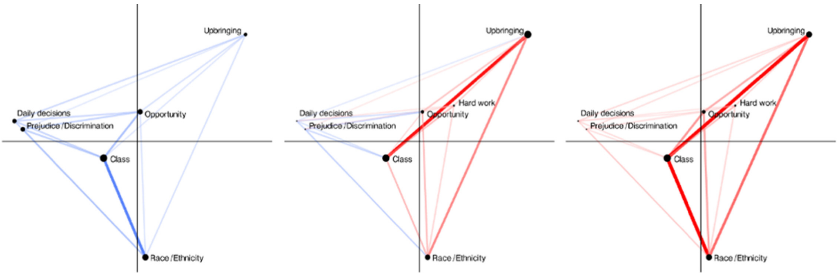

Fig. 1. Mean discourse networks for Tufts (left, blue), KSU (right, red), and a difference network graph (center). X-axis MR1 (16.8%), Y-axis SVD2 (16.9%). (Color figure online)

followed closely by connections between class and race/ethnicity and between upbringing and race/ethnicity. Many of the Tufts student emphasized the ways that race and class work together to reinforce inequity (what some would call "intersectionality"). The KSU students were more focused on what they perceived as the different behaviors of people from higher and lower socioeconomic background, and they disagreed about the reasons for those differences.

In the difference network we can see a noticeable red triangle of connections between upbringing, class, and race/ethnicity were more prominent in the discussion at KSU compared to Tufts. This is the case in spite of the fact that the strongest connections in the Tufts network is between class and race/ethnicity. The only connections that were more prominent in the Tufts network contain prejudice/discrimination or daily decisions.

Fourteen of the twenty-one (66%) possible connections among the concepts were stronger in the KSU network graph. This is reflected in fourteen lines being red and seven being blue in the difference network. These results align with our overall observation that the KSU discussion contained more diverse views. This network analysis and preceding qualitative account of student deliberation allow us to interpret the following statistical results.

Figure 2 shows the plotted points which correspond to individual student discourse networks from the social determinants of health deliberation. The points for students from Tufts are in blue and the points for students from KSU are in red. (Some points in the graph are overlapping, so the total number of visible points is less than the total number of data points.) The squares are the means of the points and the boxes around the squares are 95% confidence intervals on both dimensions.

There was a statistically significant difference between the mean of the plotted points for Tufts students compared to KSU students along the x dimension, which, as above, represents *personal beliefs versus upbringing*. A two-sample t test assuming unequal variance showed Tufts (mean = −0.384, SD = 0.124, N = 13 was statistically significantly different from KSU (mean = 0.143, SD = 0.197, N = 35; $p < 0.001$).

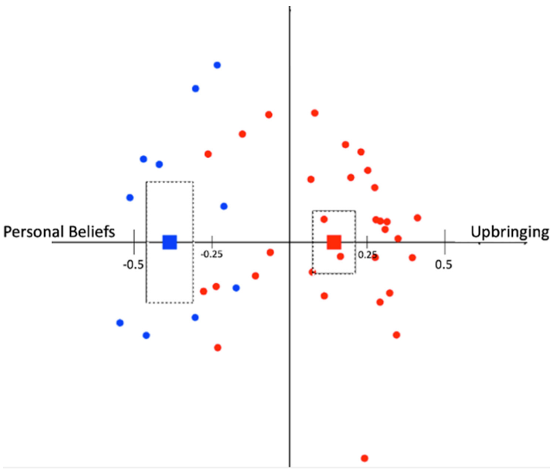

Fig. 2. Plotted points – Tufts in Blue and KSU in Red. (Color figure online)

5 Discussion and Next Directions

The differences revealed by the ENA have face-validity in the sense that they are consistent with our reading of the interview transcripts and our understanding of differences between the two courses, particularly the greater ideological diversity at KSU and the more extensive treatment of social determinants of health at Tufts. In brief, KSU students debated whether or not people are responsible for their own health because of bad behavior and problematic upbringings. Some credited good health to personal characteristics, such as hard work. Tufts students did not air those explanations but shared the view that public health is a function of social circumstances.

What should we make of the differences between the two groups' conversations? We could turn to the students for assessments, but we would find only small differences. In both groups, students reported after the discussion that the topic was important, that they had carefully considered others' views and understood what other people said, and that others had understood them. In both groups, students reported that the discussion had helped them to understand the topic, although mean responses to that question were somewhat stronger at Tufts than at KSU. Tufts students felt more strongly than KSU students that our democracy would be stronger if more people experienced this kind of discussion. Tufts students were less likely to observe a lot of disagreement within their group than KSU students were. KSU students were more likely to say that the topic of social determinants of health is important.

A great deal of evidence from the social sciences supports the consensus view in the Tufts classroom, that race and class do affect health outcomes [8, 26]. Thus, one could argue that the difference in the two discussions was a greater degree of sophistication or awareness among the Tufts students. However, this focus might not have been due to students' educations, backgrounds, or institutions. The Tufts course was more focused on health equity. Or, one might conclude that the Tufts conversation was better because it began with a factual premise: students explored nuances and applications of this premise while also increasing the cohesiveness of their group.

On the other hand, as measured by ENA, the Tufts students did not make as many connections across as many topics or ideas as the students at KSU did. Tufts students did not grapple with, or even experience, a set of opinions that came up at KSU and were incorporated into a more complex epistemic network for the class as a whole. (Because ENA compares means for the groups, the differences in the number of participants and number of comments would not matter.)

One implication for instructors may thus be that existing disagreements within a class can serve as "deliberative asset[s]" [23]. Topics on which the students happen to disagree provide better practice for deliberation. From this perspective, a drawback of the Tufts conversation was the relative homogeneity of opinion. When a group is focused on a relatively small number of issues, it may be worth choosing readings and other prompts that expand the range of ideas that the students can incorporate into their arguments.

On the other hand, some ideas are inconsistent with current academic consensus. The KSU students were not taught about social determinants of health, but if they had been, they might have restricted the topics they discussed. That suggests a possible tradeoff between scholarly expertise–learning to think like a specialist–and deliberative complexity.

In the end, judgments as to quality of deliberation require normative principles; however, our analysis here shows that these network analyses accomplish two important steps toward the ultimate goal of evaluating deliberative discussions. First, the analyses reveal aspects of the conversation that pose normative issues, and thus could lead to the development of principled assessments. Moreover, the network analyses provide quantitative metrics that could be used to implement such assessments. This paper provides just one potential analytical approach in this arena and suggests a few logical next steps.

First, ENA (as presently developed) treats all codes alike. That assumption underlines the mathematics of the method. ENA yields insights into complexity and connectedness but may overlook the fact that certain ideas are logically related in various ways. For example, to believe in the impact of race on health is the *opposite* of disbelieving in it. At Tufts, everyone who invoked race did so to emphasize racial injustice. At KSU, some commented in favor and others against this idea. Current applications of ENA do not consider relationships such as oppositeness, which would be a useful next step.

Another next step would be to use ENA as a way to model how students are influencing each other through the interactions of their discourse networks. These steps would advance the method of ENA itself and could prove valuable in the study of political deliberations more broadly.

As noted earlier, we collected simple social network metrics from the students. Integrating social network analysis with ENA would be another step.

Finally, such methods must be tested on larger samples and not merely with US undergraduates discussing issues for academic credit.

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