# The questioning lens as research tool: the social shaping of network visualisation boundaries in the case of the U.K. junior doctors' contract dispute

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# The questioning lens as research tool: the social shaping of network visualisation boundaries in the case of the U.K. junior doctors' contract dispute

Social media and the data it produces lends itself to being visualised as a network. Individual Twitter users can be represented as nodes and retweeted by another Twitter user, thereby forming a relationship, an edge, between users. However, an unbounded network is a sprawling mass of nodes and edges. Boundary settings are typically applied, for example, a time period, a hashtag, a keyword search or a network sub-structure of a phenomenon of interest. Thus, the particular visualisation created is dependent upon the boundaries applied, enabling productive visual consumption, but concealing its social shaping. To explore this question of boundary setting and its associated issues, we draw on an example from the Twitter discussions about the U.K. Minister for Health, Jeremy Hunt and the media debate surrounding the contractual hours of junior doctors during 2015 - 2016. We discuss the role and impact differing stakeholders have in setting these boundaries. We seek to provide a set of 'questioning lenses' in which we ask why these boundary settings were selected, what effect they have, and what are the potential implications of these boundary setting techniques on the visualisation consumer.

Keywords: Information Visualisation; Social Network Analysis; Medical Sociology; Data Analytics

## Introduction

Comprehending patterns in large datasets, such as the 350,000 tweets created each minute, exceeds humans' cognitive capacity, compelling the use of 'sense-making' visualisation (Manovich, 2011). However, these are often taken at face value, with little discussion of the multiple decision-making steps involved in creating and selecting a particular visualisation over others. Even simple decisions, layout and colour, can become barriers to understanding visualisations (Combs & Bederson, 1999). These "barriers cascade to later stages; they are iterative; they are user-driven and/or system-driven; and they are uni-faceted or multi-faceted" (Li et al., 2010, p.557). In commercial contexts, the visualisation consumer needs to inspect the raw data, while in academic spheres publishers are implementing data sharing policies and repository requirements. Consumers with strong quantitative skills can unpick images; however, for those who lack expertise and time, there needs to be greater transparency as to the decision-making process within the production of the visualisation. This paper illustrates the complexity of this process, by examining the NHS junior doctors' contract dispute on Twitter (samples of data from October 2015 to May 2016).

This paper contributes to the debate regarding data transparency and ramifications of the design decisions and politics of design (DiSalvo, 2014) by providing a practical example of unpicking visualisation production. By applying the Ostinato Model (Huhtamäki et al., 2015, 2017) to a sample of healthcare data, the process of producing a network visualisation becomes unpicked and the implications of different decisions and choices become clearer. This gives readers a practical example of how the model can be applied, as well as the academic questions discussed during the research process and how differing visualisation decisions affect the visualisation produced.

The Ostinato Model (Huhtamäki et al., 2015, 2017) is an iterative, user-centric, process-automated model for data-driven visual network analytics applied to a number of contexts (Aramo-Immonen et al., 2015, 2016). Unlike other process models (Bendoly, 2016; Hansen et al., 2012; Heer & Shneiderman, 2012;Pirolli & Card, 2005), it specifically addresses network visualisations for Social Media data. The model has 14 steps within two core processes, grouped as 'data collection and refinement' and 'network construction and analysis', which feedback on each other. The steps will be familiar to both quantitative and qualitative researchers (for example the first step is entry indices collection).

**Transparency of Information Visualisation**

Data are always constructed through their extraction, production and consumption (boyd & Crawford, 2012; Bowker & Star, 2000; Gitelman, 2013; Kitchin, 2013). Traditional quantitative methods focus on validity and relevance using accepted statistical equations and modelling techniques. This standardises the assessment of the preparation, collection, integration, reflection, and action of data (Isenberg 2013; Lam et al., 2012). Big data also demand data visualisation of the compleat phenomena, which raises novel methodological considerations, as these are not 'pure' reflections of the world, but a created construction of reality. How the decision-making process shapes visualisations is well researched (Lloyd & Dykes, 2011; McKenna et al., 2014; Sedlmair et al., 2012;Shneiderman & Plaisant, 2006); however, there is a need to connect visualisation design decisions with creative and reflective design practice. What is clear is that this social construction of information visualisation is opaque to the person who looks upon the visualisation and may never be questioned or known, as Rettberg (2016) comments, data can appear 'beyond argument' in its representation of the world. Data and visualisation of that data are as such designed, constructed and situated in a social role and boundary creation (Crabtree & Mortier, 2015). Visualisation, therefore, can present phenomena from a particular point of view (Elsden et al., 2016). For this reason, it is critical for users to examine visualisations with a 'questioning lens' (Dörk et al., 2013) as this encourages exploration of the data.

The concept of questioning lenses has primarily been used within commercial design to capture the different questions that frame the product from a business (viability), consumer (users needs to be met) and delivery (feasibility) view. The questioning lens differs depending on the use and users of the visualisation. In cases where its creator is the only user, the lens is a single user-based; 'does it do what I want?' However, when the visualisation has multiple users, each processes the image from their own perspective and produces multiple, often competing, roles and multiple questioning lenses. The numerous perspectives and stakeholders feed into the production of the visualisation, and creation and interpretation of the visualisation can become an area where their worldviews collide. The questioning lens becomes a research tool, producing new hypotheses and research trajectories. Multidisciplinary research teams can harness their differing worldviews to result in complex and intertwined relationships, in which the visualisation becomes a boundary object. However, often, team-based research is located within a hierarchical employment context that can close down this debate. In this case, the research team sought to harness the activity of visualisation, as a way of overcoming geographical distance and disciplinary barriers, and to share questioning lenses. Different are questions linked to the various steps, and various lenses applied: technician, analysis, theorist, external academic audience, journal reviewer etc. This paper described how we created network images, making transparent the workings behind our 'sense-making' visualisation, and collaborating by sharing what we saw when looking at the visualisations through our questioning lens.

## Methodology

To undertake the visualisation process and to reflect upon design choices, an Action Design Research methodology (ADR) (McCurdy, Dykes, & Meyer, 2016; Sein et al., 2011) was utilised. ADR supports the complex human-centred nature of the design process during the solving of real-world problems. Following the principles of this framework (see Seinet al., 2011) we captured the actions that disrupted users' processes or understanding (McCurby, Dykes, & Meyer, 2016). The authors began to discuss public perception and the role of the media while researching NHS provision and avoidable admissions into Accident and Emergency (Pinkney et al., 2016), forming the first stage of ADR, 'problem formulation, grounding design in theory and real-world problems'. These discussions led to the research aim to explore the role of mainstream media and the use of social media in medical settings; such as the increasing coverage of the U.K. junior doctors' contract debate on Twitter. During the second stage, building, intervention and evaluation, we discussed the research question, the data extraction, exploration and analysis cycle, every two weeks over a 6-month period that lasted for an hour at a time. SJE carried out the data extraction with both engaged in the exploration and analysis. Questions occurring during the discussions were logged (see Table 4). During stage 3, reflection and learning, we reflected upon the model, presenting the research to date at The Culture and Politics of Data Visualisation conference in Sheffield in October 2016, and this provided feedback and additional questions. We entered stage 4, formulation of learning, by using the conference slides as an initial paper outline and entering into further reflections and discussion about the process (~8 hours). We asked a series of questions during each phase of the Ostinato model (Huhtamäki et al., 2015). Table 4 results in the documented questions that helped us to learn as we conducted social media research using the model.

**Junior Doctors' Contract Debate**

In 2016, there was increased media coverage regarding the contract dispute between the U.K Government's Secretary of State for Health and National Health Service (NHS) Junior Doctors. The junior doctors employment contract, introduced in the 1990s, was being renewed and early negotiations were tense and paused in 2014, at which time the British Medical Association represented the junior doctors in opposing the contractual changes advocated by Jeremy Hunt. Hunt claimed in the media that a lack of adequate weekend staffing led to avoidable deaths and the junior doctor contract became an increasing focus of media attention. In 2015, the conciliation service, Acas, restarted the process and the new contract was to be imposed from the summer of 2016 (announced in February 2016), with strikes occurring at various points in 2016.

This paper we describe how we visualised the twitterscape, rather than the findings specifically. The research focuses on the hashtag, #JeremyHunt', used during the U.K. junior doctors contract dispute which ran from October 2015 to May 2016. Supplementary data using the hashtag '#Iminworkjeremy', were also collected between the 11th October 2015 and the 14$^{th}$ May 2016. The #JeremyHunt data from 16$^{th}$ February 2016 to 22$^{nd}$ February 2016 are visualised to illustrate the implications of different choices and decisions that constructed the network images. The network visualisations were used as research 'evidence' and as prompts within internal team discussion and wider academic dissemination (Freeman, 2000). Figure 1a, 1b 1c are visual representations of the same data set; that is, lesser and greater versions of the common process of packaging value-laden decision-making in reporting the Twitter research.

Figure 1a shows a network visualisation of the Twitter data referencing the hashtag #jeremyhunt during a set time frame. The nodes (circles) are Twitter actors, and the edges (lines joining nodes) are relationships between IDs, such as retweet, answering. This snowstorm of information excludes tweets to which no one responded, which, if included, would be disconnected nodes. Indeed, tweets will have appeared on the tweet account followers and may have been read, but they did not prompt the ‘follower’ to retweet or respond directly. So, this visualisation shows Twitter accounts that have entered into the discourse and gained a response from another Twitter account (n=694).

Figure 1b lets us ‘see’ the Twitter network with the lines linking clusters of tweets, and the isolated (i.e. tweets not responded to) orbiting the network. However, as will be detailed later, a range of steps have now been applied that follow the Ostinato model (Huhtamäki et al., 2015). Our questioning lens prompted questions (table 4) from this visualisation. The diagram draws the reader’s sight to the main group, labelled with the Twitter ID ’38 _degrees’, which seems to resemble a starburst cluster and we might also consider the quantities of twitter actors elsewhere in the image. We are also likely to ask how ’38_degrees’ relates to other Twitter actors and how different actors supported which ‘side’in the contract negotiations.

Figure 1c focuses our attention on the Twitter network, with lines linking clusters of tweets. The core differences from Figure 1b are the removal of the isolated tweets, the greater use of colour to demarcate clusters and more labels associated with those nodes with greater centrality in the network.

The research aimed to understand the role of the media and its relationship with grassroots activism in Twitter discussions surrounding the issue of the NHS junior doctors contractual hours dispute. We expected to see mainstream media appearing centrally in the Twitter network, with politicians and journalists referencing mainstream media to increase the impact of their tweets (Enli & Simonsen, 2017). Through the use of a hashtag that was not 'loaded' with meaning outside of healthcare government policy, we wished to observe the presence of ‘collective action’ (Bennett & Segerberg, 2013; Kavada, 2015). Whereby “participants engage with issues largely on individual terms by finding common ground in easy-to-personalise action frames that allow for diverse understandings of common problems to be shared broadly through digital media networks” (Bennett, Segerberg, & Walker, 2014, p. 233). We hoped to see grassroots activism as identifiable clusters in the network in the network visualisations presented.

Figure 1a. Data visualisation of hashtag #JeremyHunt: No layout algorithms applied (n=1737 vertices/nodes/tweet accounts, x =2460 edges/tweets/replies/mentions),

Figure 1b. Overall network diagram using the Force Atlas and Label Adjust algorithm

Figure 1c. Network diagram (ForceAtlas2 with Degree Centrality of node size and label).

**Applying the Ostinato Model**

Figures 1a, b and c evidence how the decisions taken by the human constructor of information visualisation are critical to the resulting product and the questioning lenses. To unpick this fully, we now work through the steps of the Ostinato Model (Huhtamäki et al., 2015).

*Entity Index Creation and Entity Index: Steps One and Two*

Network analysts and visualisers are faced with a number of options at the entity index creation stage. Extracting data from Twitter can be done in three ways; by searching for a specific term, following an individual, or searching for a #hashtag or 'tags' of a person/event/concept. A combination of these different methods is possible. We were guided by our intention to use the data for a network analysis, where nodes are going to be formed based on Twitter accounts. In this case, the data define the visualisation and the decisions about which data are included or not is fundamental. Similar to all methods, during data collection the researcher seeks to gather data which will answer their academic research question. However, unlike typical quantitative methods, where the boundaries are defined before collection, 'scraping' or 'crawling' Twitter requires 'fore-knowledge' of the likely network which will come into existence from the tweets/data points. We were faced with different ways of constructing the data set; by key term (i.e. by searching for 'junior doctor'), particular users (i.e. following the accounts of the BMA or the NHS), or by responses to specific accounts (i.e. searching for @BMA or @NHS). Twitter also enables researchers to search using #; 'tags', which users can use to index their tweets within the Twitter-sphere (i.e. #JuniorDoctor). A fundamental difference exists between these search pathways - the first set (keywords, etc.) taps into the recognised worth/value of the term. The second set, hashtags, taps into the future 'expected' value, which may or may not come to pass within the seven day backwards search enabled through the REST api. Researchers need time to identify a topic as 'trending', at which point the early stages of the network could be disintegrating. The researcher needs to ask many questions of the data when choosing a search method, such as the implications of changing the Twitter search criteria and the effect that this may have. The hashtag method is more appealing for network analysis because it captures the network formation 'in action'; however, this will require multiple collecting, as many extractions will not bear fruit. For example, Table 1 shows how collecting using the hashtag #jeremyhunt and the hashtag #IaminworkJeremy produced vastly different datasets over the same time period.

Table 1. Example of Entity Index Creation based on two hashtags considered in the initial stage as possible focuses (16th to 22nd February, 2016).

There is a core difference between node relationships when formed by hashtag data and that of, say, replies to an account (via @) and this impacts on the agency contained within the nodes. We selected hashtag collecting as it enhanced the entity index creation stage within the visualisation process, giving the originator of the data (tweeter) some control over the network relationship formed. Simply stated, the tweets from Jeremy Hunt's account are clearly intentional, the replies (via @) are direct responses to this Twitter account, but hashtags are user-applied tags directly on the data. Agency is not limited to humans, and it is important to recognise the activity of Twitter bots in this context. Hashtags enable the Twitter account user to 'lend their voice' to a particular current Twitter discourse. By designating one or more hashtags, the author can have some control over the network boundaries. It also, critically, shows evidence of 'trending'. In this case, the creation of an individual's name as a hashtag was a critical feature of the network.

Early in the research process, we identified that grass-roots objections could be accessed using a hashtag string, such as #iaminworkjeremy, which related to national media discourses over the impact of weekend working regulations and BMA strikes on the NHS hospital cover. 'Local' hashtags were also in use, for example, using hospital names. Thus, the choice of search criteria is the first decision that affects the network; by its very nature, it will exclude nearly everything and only include the communication of interest.

This initial stage requires comfort with a 'trial and error' approach to reform the search criteria, which is easily achieved by searching for items such as '#jeremyhunt', '#jeremy_hunt', @jeremy_hunt and @jeremyhuntnews. There are limitations to the use of hashtags and using them for searching Twitter, as the network visualisation analyst decides which hashtag to use. Some research areas are not easily 'hashtag-able', for instance side effects of medication, generalised sentiments or expressions with compounded issues or an unidentified root-causes. For example, using #Iminworkjeremy, or #jeremyhunt did not capture the voices of patients, or tell us how junior doctor strike action impacted patients. The selected search criteria will completely affect the overall network visualisation, and affect future decisions about how the network should be displayed. At this stage, we narrowed our research focus to the social media communication surrounding the U.K.'s cabinet minister for Health and used the hashtag '#jeremyhunt' because it did not carry a specific positive or negative frame of reference for Jeremy Hunt. Only after the data were gathered and analysed could we see that this 'neutral' tag produced a network where, out of the 10 most centralised Twitter actors, seven were distinctly associated with contesting the new NHS contractual arrangements.

The limitations of extracting Twitter data means that network researchers will not be able to go back in time and choose a different search term to apply to Twitter unless they ran multiple extractions. A bottom-up, grounded, ethnographic understanding of the data is necessary to formulate extraction criteria that appropriately target the data in question.

### *Crawling, Scraping and Aggregation: Steps Three to Five*

Having decided to focus on the hashtag '#jeremyhunt', we progressed to the next steps of our research journey. Crawling, scraping and aggregation (referred to here as collecting) can seem unidirectional and linear when grouped together. However, they are a cyclical process that feedback on each other. We used NodeXL to extract the linked data, and this can be undertaken in a range of ways; from simple document readers to web crawlers with full functionality. Once the data are collected, they can be scraped; "distilling data from documents that are published to the Web for humans to use" (Huhtamäki et al., 2015, p. 210). However, this extraction and filtering process has many dependencies on the tools used. For instance, a basic extraction using NodeXL limits the number of tweets to 2,000. Furthermore, Twitter APIs (Application Programming Interface supplied by Twitter for developers) such as the REST API has a rate limit of 180 requests per 15 minutes over the previous seven days. These limits have a bearing on the findings (such as sample sizes,  restricting some conclusions), and this should be acknowledged.

At this point, it is advisable to collect additional information sources, such as geographical information, time-based information and demographic information that can be used as attribute data and are also useful in visualising the networks. Unlike pure deductive quantitative research, questions are likely to develop and augmenting data required as researchers engage with the questioning lens produced by seeing the visualisation. Thus, while straightforward extractions can provide individual entities sufficient for analysis of relationships, this only gives one perspective, and a combination of data sources gives a stronger argument that is more complex and nuanced. In our research example, Table 2 shows additional data we collected from Twitter profiles and which were important for understanding the IDs/nodes and those ranked as most central in our network.

Table 2: Step 5 Aggregation: Degree centrality of highest ranked nodes in network

Additional information also impacts on how the network is visualised and produces a greater understanding of differences between clusters. For example, compare the visualisations in Figure 1b and 1c. 1c highlights clusters by using differences in colour; however, understanding those clusters requires further information. Network nodes can be grouped visually by using the same colour to identify nodes that share a particular feature. In our research, we were interested in the role of the mainstream media in social media discussions of the junior doctors contract debate, and we could have grouped nodes from major media outlets in the same colour or by political leaning. However, we would have required additional sources of information. We have not visualised this, as only one of the most centralised nodes in the network was a mainstream media outlet, the Times newspaper, a British broadsheet newspaper with a conservative political leaning. The tenth most centralised Twitter actor, Peter Brookes, is a cartoonist for the Times. Sunapology (third most highly centralised Twitter actor) refers to another newspaper, the conservative tabloid The Sun. Here we see the value of gathering the additional information, as their profile explicitly states the ID’s stance towards the newspaper.

***Proxy and Filtering in Entities: Steps Six and Seven***

Cleaning (removing duplicates, tweets from bots/spam, and tweets returned because of synonyms) is critical for two reasons. First, it is necessary to exclude irrelevant data (synonyms, etc) as they will render the visualisation noisy (random error) and could overwhelm the viewer. Second, the returned data can have errors caused by unknown and unpredictable changes on the Twitter software platform. The data can exhibit a bias (i.e. a systematic error will have a direction/opinion), which can sometimes be very obvious, and in other instances not (Baeza-Yates & Maarek, 2012). If it is not identified, it will skew any resulting analysis and visualisation, and that bias and tendency should be discussed.

In small sample sizes, the data can be cleaned to exclude data that do not address the research question. The time required to identify varies, for example, it is a relatively quick task to determine duplicates by rearranging the data file, while synonyms require the assessment of each single tweet. In large data sets, it will be far too time-consuming to carry out a 'deep' clean of the data and, if data are large enough, it may suffice to ignore entities that are not appropriate. They can be insignificant in number and have little impact on the overall research in terms of the algorithms and calculations carried out.

In this case, SJE used approximately 20 hours to read this fairly small-scale Twitter dataset. While automation and the use of algorithms can offer labour-saving tools, it depends on the size of the dataset. In this case, manual cleaning was less labour-intensive than programming because Twitter has a sizable number of 'spam bots' that can be very creative in the ways they bypass spam filters and complex programming is then required. However, while the data set was cleaned to the level of network analysis and visualisation, it was not sufficient for qualitative analysis of individual tweets, and this can cause conflict when different team members seek to use the data in differing ways.

***Node and Edge creation, Metrics calculation, and Node and Edge filtering: Steps Eight to Ten***

*Entity Index refinement*

Once the data have been cleaned and filtered, the nodes and edges in the network can be identified. As we showed in Figure 1b and 1c, social media, and the data it produces, lends itself to being visualised as a network, as individual Twitter users can be represented as nodes and being re-tweeted or mentioned by another Twitter user forms a relationship, an edge, between users.

Table 3. Different Twitter-based node and edge types

We use individual user accounts as the nodes and re-tweeting and mentions behaviour to form edges. However, we could have tracked hashtags via followers of Twitter accounts. In the future, we will look to see if hashtag references to #jeremyhunt are positive or negative in tone.

*Metrics Calculation and Filtering*

Metric calculations are the set of mathematical tools that can include the calculation of centrality, clustering, cohesion, reciprocity, homophily, density, etc. Each of these concepts, like centrality, can be calculated in different ways, depending on which aspect of the phenomena the researcher is concerned with. It is critical to understand decisions about which tool(s) to apply will affect the results of the metric calculations regardless of our (later) choice of layout for the visualisation. For example, in our case study, we assessed how ‘central’ the nodes were and plotted the size of the node in relation to their centrality measure, and the choice of network measure directly affects what is shown. For example, in Figure 1b and 1c, 38_degrees is a larger node than sunapology, because the twitter actor is more ‘central’ to the discourse as calculated by degree centrality, not because it issued more tweets. We can see how this shapes the visualisation by comparing 1b/1c to Figure 2, which uses a different centrality measure (degree centrality versus betweenness). Our analysis shows that 38_degrees has a higher level of prestige in the network (higher degree centrality) than others, which may act as a gate-keeper to different sections of the network (calculated via betweenness centrality). It is also critical to note that some calculations are susceptible to self-promotion, such as a tweeter sending a number of tweets mentioning several other tweeters. Future work will question whether the most appropriate metric has been applied to the data.

Often the data themselves direct the choice of metric calculation. The choice of metrics will be restricted by the network data in question (one/two mode networks, directed/undirected data, valued/binary). However, the choice of metric calculation is normally based upon the decisions of the network researcher: which calculations they may be familiar with or that they rightly or wrongly feel appropriate. Those decisions are not based on any choices from the originator of the data, or the end user of the visualisation, unless the visualisation viewer is the researcher themselves, which is often the case. The choice of metric should be based upon its appropriateness to the data and in providing a convincing response to the research question and building upon previous studies.

We chose centrality measures (popularity – in-degree) to ascertain whether mainstream media appears at the hub of the network. In the case of the data presented in this paper, mainstream media does not appear centrally. We also wished to cross reference the degree centrality findings with other centrality measures (betweeness and PageRank) to see if mainstream stream media bridged different groups (e.g. activist groups and Jeremy Hunt); we did not find this to be the case, either. We also chose to apply modularity clustering to the network (with each cluster associated with a colour). In the network visualisation (Figure 1b), clusters can be easily identified. For instance, 38_degrees can be seen as one large cluster wherein many other people are retweeting or mentioning them. This political action group can be seen as central to the "collective action" in support of junior doctors during the dispute. Their high centrality score also confirms their "collective action" role.

Figure 2. Network diagram. (ForceAtlas2 with Betweeness Centrality of node size and label). The insert from Figure 1c shows the area of the network that shifts because of centrality measurements.

***Layout Processing, Visual Properties Confirmation, Visual processing: Steps Eleven to Thirteen***

These stages aim to produce the visualisation for viewing. The data are laid out, the properties configured and displayed for the viewer's consumption. This may not be the final visualisation, as various viewers may well suggest alterations after viewing it; in which case, the cycle will repeat until the point in which the researcher believes that the visualisation tells the story that they wish to convey.

As mentioned in the discussion of Figure 1a, when first accessed through visualisation software, the network is a mass of nodes and edges, and, even if those entities are refined, it still requires algorithms to be applied to the network data. In the case of the '#jeremyhunt' data, this is achieved via a software package such as Gephi (Bastian, Heymann and Jacomy, 2009), an open-source network analysis and visualisation tool which was created by students of the University of Technology of Compiègne in France. This offers 12 possible layouts with other network visualisation programs having far more. Each of these layouts uses a different algorithm, which has a bearing upon how the data are visualised and the focus of that visualisation.

Through various rounds of exploring the data, we also explored how the Yifan Hu algorithm displayed the data (see Figure 3). Comparing these visualisations highlights how the slightly different visualisations show greater clustering in Figure 1c, but clearer visualisation of the specific nodes in Figure 3. The core difference is the increased use of colour (blue, red, purple). Comparing these, we questioned movement and directionality in the network (e.g. which nodes formed first, did the network move inward or outward, etc?)

Within the Ostinato model (Huhtamäki et al., 2015), these three steps form the few unidirectional and linear steps in the model. In processing a nodes are given a position in two-dimensional space in a way that produces ‘understanding’ to visual consumers of the network structure. That understanding may result in a visualisation that is more ‘readable’ or more pleasing to the eye (as subjective as this is) or, hopefully, a combination of both. Figure 3 is arguably more attractive than Figures 1a, b and c, and perhaps it is more readable also. However, each visualisation has different strengths; the ForceAtlas2 layout (Jacomy,Venturini, Heymann & Bastian, 2014) in Figure 1c reveals more of the clustering that occurs in the network, but does not show the individual entities in the same way that Figure 3 or the highly detailed Figure 1b achieves.

Figure 3: Network diagram. (Yifan Hu with Degree Centrality of node size and label).

*Visual Properties Configuration*

At this reflective stage, initial ‘draft’ visualisations are considered; with adaptations to the network often made based on the metric calculations. Again, researcher knowledge about the metric calculations and how they were utilised in the visual properties of the network is key. The network display will inevitably be the result of the abilities of the researcher in transparently questioning the data and in producing visualisations that address the research question. In the junior doctors debate, certain measures were chosen over others: centrality and clustering because they addressed the research question, but also because of researcher familiarity. The choice of research questions is also often linked to the confidence of the researcher in being able to answer them using their own knowledge. In the junior doctors case presented here, Figure 1b shows the use of two metrics: PageRank and Degree Centrality.

The visualisation in Figure 1b shows node size based on degree centrality (general activity, both indegree and outdegree) of a node. Node colour is based on PageRank (connection to the key individual IDs in the network) with a heating colouration for low levels of PageRank being closer to blue and higher levels being red. The figure shows that 38_degrees has high degree centrality and connects to strategic IDs in the network. However, the node jeremy_hunt has relative high degree centrality, but lower levels of PageRank (strategic positioning of Twitter accounts which reply or mention jeremy_hunt). We can also compare Figure 1c with Figure 2, in which degree centrality is compared to betweenness centrality respectively. Although 38_degrees has high popularity (particularly in inDegree – Twitter accounts replying and mentioning them) and has high PageRank (strategic IDs in the network replying and mentioned their tweets), it does not span different pockets of communication in the network as well as others.

Space is a key limitation in visual network analysis, both for on-screen viewing and hard copy visualisation. Depending on the level of detail required in the analysis, hundreds or thousands of nodes can be presented in one visualisation view. This results in a series of questions about looking at the whole network (and what constitutes the whole) or the sub-structure such as clusters. This allows for greater interrogation of those nodes, but no less understanding of the greater interconnectivity of the network.

### *Visualisation Provision*

We used the Gephi software package for our visualisation and clarity and showed the reader these images earlier in the paper. Different software packages have different features (i.e. dashboards or analytical tools) and each of these types of technology will enable the viewer varying degrees of adaptability. Like NodeXL and Netdraw, Gephi has a set of full-feature explorative analytics tools that viewers can use to adapt the layout and configurations of the visual properties. Different conversations and questions about the visualisations and data will occur based on the type of software tools used, and researchers will adapt the network in relation to this. Once the visualisation process has begun, there is an iterative refinement process which involves considering how to improve clarity, for example by removing nodes or providing additional data to provide a more accurate picture, such as the role and association of outliers in Figure 1c. Whatever stage the refinement process occurs, questions need to be asked as to why entities have been deselected and are not visible (for example, isolate nodes may not be of interest), or why additional information is needed.

### *Sense-making and Storytelling: Step Fourteen*

The final step is sense-making and storytelling. Information visualisation includes data transformation, representation and interaction; it is ultimately about harnessing human visual perception capabilities to help identify trends, patterns and outliers (Huhtamäki et al., 2015). Two questions need addressing. First, for whom is the visualisation intended? The answer will affect whether the trends and patterns that are presented address the questions the users have of the data. Second, are these identifiable patterns presently appropriately? If so, they should provide the user with knowledge and value. The visualisation in our junior doctors debate case study was from a prompt for research discussions around the role of the media. The visualisation, in this instance, becomes a prompt for academic discussion and to help form hypothesis. These questions of knowledge and value in design decision-making emphasise the process of doing and thinking, akin to Schon's reflection-in-action concept, whereby the design process and design decisions are intricately interlinked (Schon, 1984).

## Producing Questioning Lenses

We used different questioning lenses during the various steps in our research; technical, methodological, analytical, theoretical, promotional, etc. Table 4 highlights a few of the questions raised by using different lenses. These overlap, as the answers depend on which lenses were used. Table 4 identifies what was learned during the process of applying the Ostinato model to this particular case study and aims to give practical questions that can aid other researchers in gaining insight. Future work will look to **i**dentify potential biases of different lenses, and how multi-disciplinary researchers take agency from each other's lenses. Additionally, future work will consider what biases occur at what stage and at stage transitions, and what measures are needed to clarify those biases.

Table 4. Applying the questioning lens to visualisation

## Conclusion

We have looked at the process in which visualisations are made, by providing a case study of the junior doctors Twitter debate as an example of the decision-making that occurs through the visualisation process. The paper has explored and discussed the decision points of the network visualisation process in order to open up the discussion about assumptions about the 'end product' of a visualisation and the need to understand how it was constructed. The Ostinato model was applied to healthcare social media data, highlighting potential questions posed of the data and their display. We outlined the decisions taken during the information visualisation design process and addressed the issue of why certain design decisions have been made and addressed the lack of guidance that helps visualisation designers navigate the reality of the visualisation design process (McKenna et al., 2014).

The Ostinato model gave transparency to the junior doctors contract debate data and visualisation and allowed us to explore the role of mainstream media in the junior doctors debate. Highlighting how the mainstream media is not the main source of data propagation, but rather charitable lobbying groups such as 38-degrees are the main communication nodes during the research timeframe in question. This may suggest "citizens are said to be able to challenge the monopoly control of media production and dissemination by state and commercial institutions" (Loader & Mercea, 2011, p. 759). In addition, while the process was iterative, it is not clear how the visualisation adapts when one enters the model at different points, and what impact this has on the final design. It is possible that there is a difference between working through the early stages, such as data extraction, with and without the aid of a visualisation prompt. Future research could consider testing different approaches to the model to indicate an 'optimum' pathway for social media data extraction and network visualisation. Further research is also necessary to explore sentiment forming within the network, such as considering hashtag endorsement or contestation of the contractual hours dispute (Lycarião & dos Santos, 2017).

In shedding light on the role of decisions, this paper continues the call for and discussion of transparency when using network visualisations of Twitter data. We have shown the methodological process of SNA visualisation in relation to healthcare data, and argue that social science relational data should be transparent in its exploration, but also in the decisions researchers make when analysing and visualising social data. The network visualiser plays a key role in shaping the 'end product' visualisation, often through their influences and biases for certain tools. The information visualisation process is an ethnographic process of sorts, wherein the data and researcher/network visualiser intertwine. The visualisation is auto-biographical in the same way that written ethnographic accounts are, but in a less explicit way. Similarly, the user of the visualisation and the provider of the data have some role in the visualisation, as in ethnographic research. Those roles become more enhanced as the field of information visualisation develops. Future work is needed to explore ethnographic approaches, particularly in regard to the user, sense-making and data-driven triangulation (Basole et al., 2015; Battistella et al., 2013; Bendoly, 2016a, 2016b).

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