Chapter X: Towards transdisciplinary collaboration between computer and social scientists: Initial experiences and reflections

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X.1 Introduction

The aim of this chapter is to explore a collaboration between computer scientists (NS and DK), who take a primarily quantitative approach, and qualitative researchers in sociology (JB and FS) and international relations (VP and MP). This computational social science collaboration, is taking place within a large project, the *"Space for sharing"* study, which aims to investigate how online platforms support or hinder the sharing of empathy and trust amongst people in extreme and vulnerable circumstances. The collaboration between JB, FS, DK and NS is on the topic of *Digital Outreach and Emotional Distress* (Section 2); and the collaboration between MP, VP, DK and NS on *Trust and Empathy Online in Disasters and Humanitarian Crises* (Section 3). Although the two collaborations are reasonably independent of each other, there are fundamental commonalities, which we hope will provide some food for thought on the nature of interactions between computer and social scientists.

Below, we introduce the benefits of such interdisciplinary work within the emerging field of computational social science, and describe the overall context for our collaborations. Following this, we report on our two collaborative efforts (Sections 2 and 3), and draw conclusions and lessons from our experience (Section 4).

X.1.1 Reflections on Computational Social Science

The Internet has transformed the way we study human relations. Whereas we used to communicate with people directly to understand how they feel, think and behave, many of our interactions are now *mediated* by Internet-based software such as online social networks, or instant messaging platforms. Every interaction we make on such platforms can potentially be recorded, resulting in an extensive trace of our online actions and communications - a trace which sometimes can tell us more about people than they intend to reveal themselves.

Many studies have made use of data constituted through such online communications. A prominent example of the transformation that the Internet brings in studying human relations is the so-called *"small world"* experiment (Travers and Milgram 1969), which showed experimentally that people are all connected within an average of *six degrees of separation*. The original experiment involved randomly selected subjects in Kansas and Nebraska, USA, who were asked to send a letter to a recipient in Massachusetts (if they knew him or her directly), or forward it to someone they knew *on a first name basis*, who, in their opinion might be in a better position to forward the letter to the final recipient using the same rules. In the early years of this century, a team of physicists at Columbia University confirmed the six-degree of separation hypothesis on a considerably larger scale – a dataset of email conversations from 60K users (Dodds et al. 2003). Around the same time, a computer scientist Jon Kleinberg analysed the small-world phenomenon from an algorithmic perspective (Kleinberg 2000 and 2001) and was one of the first to demonstrate that people are not only connected by very short paths, but that they tend to be very good at finding those paths. The work of Kleinberg, Dodds et al., and many others since then, has pioneered a proliferation of digital approaches to the study of human relations, and transformed what once was the prerogative of social scientists into a truly interdisciplinary field, one that has been termed *Computational Social Science* (Lazer et al. 2009).

The emerging Computational Social Science literature has also cleverly used web data to test hypotheses and theories in various other areas of social science. For instance, DeChoudhury et al. (2013) analyzed depression among Twitter users by measuring behavioral attributes relating to social engagement, emotion, language and linguistic styles, ego networks, and mentions of antidepressant medications. The authors identified significant indicators of depression in social media including a decrease in social activity, raised negative affect and highly clustered ego networks. Althoff et al. (2014) by analyzing at scale an online community devoted to giving away free pizza to strangers that ask for one, attest how sociological concepts of *status and similarity* as well as linguistic characteristics of *politeness, sentiment and reciprocity* lead to requests for favours being met. In (Garcia et al. 2014) the authors conducted a large-scale evaluation of the *Bechdel Test*, which measures male bias in films by looking at whether two female characters talk about something other than men. Experiments conducted on two large online social networks suggested that Twitter conversations have a clear male bias, which is not observed in Myspace discussions.

Given the increasing number of researchers employing such methods, few would disagree that *digitalization of social science* has the potential to significantly transform our understanding of human relationships. However, large-scale analysis of digital human traces also risks the loss of direct communication with *real people* - a core feature of traditional social science. While the task of revealing and understanding complex patterns of interactions between hundreds of millions of users can hardly be done via traditional interviews and surveys, it is also true that there are limits to what can be understood about individual users' perceptions and experience without direct communication with them. Computational social scientists working within rigorous mathematical norms may avoid making qualitative judgments yet in traditional social sciences, such interpretation often yields the deepest insights.

One approach to tackling these limitations in computational science, and combining the best of two worlds, involves the creation of environments for interdisciplinary collaboration where social scientists can work with scientists from other disciplines on a common research agenda. Indeed, various initiatives including *interdisciplinary conferences* on social science (e.g., AAAI ICWSM, IEEE SocialCom, IC^2S^2), *interdisciplinary research centers* (e.g., MediaLab Amsterdam, Oxford Internet Institute, etc.) and *funding schemes* which encourage interdisciplinary research have been recently introduced.

X.1.2 Context – "Space for Sharing" ESRC project

The authors of this chapter were awarded, with other colleagues, funding of a £1.3M study by the UK's Economic and Social Research Council (ESRC). The project was commissioned in the scope of a larger funding call 'to develop a greater understanding of how empathy and trust are developed, maintained, transformed and lost in social media interactions' (ESRC 2014). Combining the research efforts of investigators from six different universities in the United Kingdom, the team comprises researchers from computer science, medical informatics, sociology, international relations, and philosophy and media theory. Transdisciplinary research across these disciplines is an explicit and fundamental goal of the 'Space for sharing' project[1] and we return to what we mean by this later in the chapter.

In 'Space for Sharing' we are working towards a joint understanding of trust and empathy among users in various extreme circumstances including disasters and humanitarian crisis and emotional distress. People in these circumstances can be extremely vulnerable, and some of them may be seeking help that could make the difference between life and death. It may be necessary to establish trust and empathy very quickly to make that difference. In such extreme situations, people may end up over-sharing information, or they may be disadvantaged by not sharing enough. At the same time, others in the online community need to know when they are responding to genuine distress.

To understand how empathy and trust mediate sharing practices in these circumstances, we have analyzed a wide range of data sources including public spaces for sharing (such as Twitter), but also more intimate communication channels (such as emails). The knowledge acquired through this analysis may transform how resources and aid are distributed on a local and global basis but also could enhance individual and community resilience. In the next two sections we explore how computer and social scientists can work together to investigate these themes in relation to two different spheres: emotional distress and humanitarian and disaster-linked crises.

X.2 Digital Outreach and Emotional Distress

The subproject, *Digital Outreach and Emotional Distress*, is shaped by the sociology of emotions and personal relationships (JB) on the one hand, and Internet and social media studies

[1] A Shared Space & A Space for Sharing - http://www.space4sharingstudy.org/

(FS) on the other. In this study, we want to understand how empathy and trust play out in social interactions around emotional distress in online spaces. How do the spaces in which interactions take place shape response, and what is different about emotional support through social media compared with other online and offline contexts?

The project partner in this collaboration is *Samaritans UK.* Samaritans is a large voluntary organisation that offers support to people in emotional distress through a variety of channels, including email. As part of its effort to engage in other forms of digital outreach, the organisation recently attempted to develop and launch a tool to help others provide support to people in emotional distress through Twitter[2]. For these reasons, the spaces of email and Twitter emerged as topical and organizationally relevant sites for the study of the digital sharing of emotions and of empathy and trust online.

The aim is to find out about experiences of emotional support via email (and to some extent via Samaritans' text messaging service) compared with other non-digital methods that the organisation has employed – particularly phone, but also face-to-face. But we also want to find out how the move toward digital outreach fits or not with the organisation's history, its nature of service and philosophical approach to emotional support. Against this backdrop, we have been working with our computer science colleagues to explore talk about emotional distress on Twitter. Key considerations have included the questions we can most usefully ask about such talk: how best can we go about collecting and analysing relevant Twitter data and what are the ethics of doing so? Some of these are questions we are still trying to answer, but we explore

[2] Samaritans Radar, a Twitter app that was designed to alert users to tweets that people they follow had made that might signal some form of emotional distress. The application proved controversial and was taken down 8 days after launch due to a number of concerns.

below three emergent aspects which might help shed light on interdisciplinary approaches to social media and big data research.

X.2.1 Balancing what is possible with what is meaningful

There is a seductive quality in working with big data: the larger the data set, the greater the possibility for developing models that are robust enough to be applied to other data sets. From a computer science perspective this is a worthwhile aim in and of itself, though from within computing science there is also a growing awareness that this aim would be enriched by social-science-informed hypotheses (Lazer et al 2009). While there are reservations about the assumptions embedded in datafication (van Dijck et al. 2014), unease around big data analysis is writ larger when what the data involved is assumed to provide a measure of 'emotions' and 'relationships'.

Sociological research has aimed to develop a more nuanced understanding of emotions – framing these as fluid, as relational, as not always expressible or even recognisable by self (see e.g. (Burkitt 2014); (Brownlie 2014)). The messiness of emotions – how they are felt, expressed and made sense of – sits uneasily with an approach that makes use of *sentiment analysis*, which attempts to quantify positivity and negativity. There are the well-recognised limits of computational understanding of the context of word use (figurative language, and sarcasm for example), but from a sociological perspective there are also epistemological and ontological problems with measuring emotions and reducing their complexity to fixed categories. Unease with the quantification of emotion is not new but what is new is the scale and predictive drive of the analysis of big data. Part of working across disciplines in this context, then, involves being aware of how we are constituting and conceptualising emotions through our research and acknowledging these constructions might be at best in tension and at worst contradictory.

X.2.2 Small Data in Big Data.

One part of our work with our computer science colleagues involves using a typology to examine tweets that are public responses to famous deaths by suicide (whether the deaths of public figures or people who have become famous posthumously). This combines domain expert-led coding of social media posts with a machine learning driven analysis of the phenomena on large scale datasets. The expertise of social scientists is drawn on in the initial stages of the analysis to develop a coding schema for classifying social media posts, but, also at the later stages when large scale quantitative measurements are conducted. An actual labelling step might be outsourced to a crowdsourcing platforms, e.g., Amazon Mechanical Turk, ClickWorker, Cloud Crowd, Micro Task, etc. The expertise required from the computer scientists lies in providing scaling mechanisms to extrapolate the results of sampled coding to the datasets of a significantly larger scale. The scaling mechanism requires a custom machine learning framework designed to recognize a labelled class from a statistical distribution and linguistic characteristics of the words which appear in the posts. It is worth noting, that similar approach has been previously used to analyze politeness in social networks (Danescu-Niculescu-Mizil et al. 2013), community response to gun shootings in the US (Glasgow et al. 2014) and understanding loneliness among Twitter users (Kivran-Swaine et al. 2014).

The above approach is consistent with a qualitatively driven approach to mixed method research (Mason 2006) as here qualitative analysis is being used as a way of improving keyword searches in big datasets. However, there are limits to the depth of the qualitative work that can take place in relation to particular tweets. For example, tweets could appear to do the work of blaming or scapegoating a particular person or organisation for a person's death by suicide but without additional qualitative analysis we cannot understand what arguments were used to make such claims, or even who or what was blamed, and how particular groups or individuals articulated these claims over time in the data.

For this reason an iterative and complementary approach to quantitative and qualitative analysis of data has been most fruitful in our project design:

a) qualitative methods provide the typology;

b) computational methods process the data into categories;

c) quantitative methods help us to find patterns in the data;

d) qualitative analysis enables us to take a cross-section of that data and understand what happened in that moment.

In the process of creating a typology, we look for emergent themes through qualitative coding. This involves zooming in on a sample of a thousand or so tweets among hundreds of thousands or even millions of tweets in the full dataset. However, there is a problem with this approach, as it is time consuming and cannot be understood in the context of the full dataset. For example, we might know that some participants called for political activism in the Twitter discussion that followed a particular death by suicide, but we do not know how widespread this was or when it began to emerge unless we attempted to code a very large subset of tweets. This is too time-consuming and difficult a task for qualitative coders to undertake over a dataset that might have millions of tweets. Computational methods then become useful because they can process the data automatically into different categories, which can then be tracked across time using quantitative methods. We could then identify a moment in time when calls for political activism increased. However, quantitative and computational methods cannot tell us *why, by whom,* or *how* these social practices were enacted, so we then need to return to qualitative analysis to understand how participants were behaving and explaining their behaviour at that moment in time. In this final stage of the analysis we can find out who is advocating political activism,what that activism involves and how participants articulated the need for this activism to others. These are the *small data in the big data*, and an interdisciplinary approach is appropriate for seeking it out.

This movement between qualitative and quantitative research reminds us that even when making data "big", the small data through which it is constituted can point to narratives that counter the big picture. This iterative approach surfaces the ways big data are constituted and contributes to those challenging the myth of big data as raw, objective data (Boyd and Crawford 2012) but at the same time it recognises that the work of processing big data allows us to find and systematically explore the small.

X.2.3 Finding the everyday

Lev Manovich argued that digital media provide us with extremely rich data for the study of everyday lives and practices:

"For the first time, we can follow [the] imaginations, opinions, ideas, and feelings of hundreds of millions of people. We can see the images and the videos they create and comment on, monitor the conversations they are engaged in, read their blog posts and tweets, navigate their maps,

listen to their track lists, and follow their trajectories in physical space" (Manovich 2012 in Burgess & Bruns 2012).

What, though, can we *meaningfully* understand about the way that people use digital media to express difficult feelings in the everyday, within the confines of the Twitter API and the methods that our computer science team has available to them to collect people's everyday ideas and feelings?

The everyday is a core sociological interest and of increasing interest to those doing Twitter analysis, but for computer scientists there are key difficulties in retrieving such data. As noted, part of our research on response to suicide has addressed public responses to well publicised death by suicide. However, a second part of the Twitter project is concerned with another kind of response: *interpersonal in-platform response* (Twitter replies) at times when a person (famous or not) has expressed emotional distress on Twitter. These are very small, very specific moments, at odds with the majority of big data research, which tends to focus on the big event or campaigns delimited by a hashtag. This has been a challenge for our team. The computer scientists in the team have devised a simple tool that finds replies to an initial dataset achieved through keyword searching. This enables focusing on fleeting, small moments of empathy (a key concept in our project) through the collection of replies and provides an illustration of how a computational solution can be found to a sociological question. In this case, how empathy happens (or not) in the everyday. We shall see some practical examples of this analysis in Section 4**.**

X.3 Trust and Empathy Online during Disasters and Humanitarian Crisis

Our second collaborative effort is looking at disasters and humanitarian crises through the lens of social media data. Big data is becoming a key theme in *International Relations* and *International Security* studies. Digital humanitarianism or the role of communications technology in humanitarian crises situations is a new important area of study. There is excitement about the possibilities offered by big data available through social media and other communications technology in mapping emerging phenomena in real time, and thereby facilitating rapid understanding of and responses to crisis situations, not just for governments but for communities. The collaboration between MP, VP, DK and NS is exploring the role of social media in building or undermining empathy and trust in conflict or disaster situations, a core area of study in International Relations studies.

Identifying the potential and limits of social media research is important for international researchers and policy-makers in the context of situations where access on the ground and traditional field analysis may be difficult. Humanitarian innovation in the area of social media and big data is a theme of the planned first *World Humanitarian Summit* to be held in Istanbul in May 2016 (UN Secretary-General, 2015). Teaming up with computer science specialists will allow International Relations researchers to explore the theoretical, practical and ethical role of social media more systematically in conflict or disaster situations. One central emerging ethical concern is over big data as a tool of enablement or *surveillance and containment* of populations.

We have chosen two case studies:

- *Balkan floods 2014*. Social media and flood disaster responses among post-conflict ethnically divided communities in Bosnian/Croatian/Serbian and English languages.
- *Ukraine conflict 2013 onwards*. Social media and responses to the Ukraine conflict in Ukrainian, Russian and English languages.

The conflict situation in Ukraine and the post-conflict disaster situation in the Balkans have certain parallels in their local and international dynamics, in so far as its participants used to be citizens of the same country, many of them know their adversaries personally, and they can communicate in a language they all understand, and where the concerns of divided communities have also become internationalised and become international security issues.

Our two case studies involve conflict and post-conflict situations, in which the challenges of the post-conflict Balkans have parallels and potential lessons for the Ukraine conflict. The Balkans have now experienced a quarter of a century of international intervention seeking to build regional peace and security. Yet the long-term international interventions have failed to achieve economic security or genuine reconciliation between the former warring parties. The Balkans experienced some initial post-war reconstruction and the successful revival of tourism in a few areas, but overall we see faltering economies, characterised by de-industrialisation, rising long-term unemployment and under-employment, state and personal indebtedness, and depopulation, where wartime ethnic population displacements are being followed by peacetime economic migration abroad. Against this malaise the negative wartime stereotypes are perpetuated in politics and the mainstream media. We see this in the recent series of divided 20th anniversary war commemorations held across the region reaffirming nationalist perspectives.

Nevertheless, the worst floods to hit the Western Balkans in a century in 2014 witnessed the galvanising of assistance in communities and expressions of solidarity between the wartime adversaries supported through social media.

X.3.1 The role of Social Media

The development of social media over the last decade offers a new communicative tool for individuals in crisis situations and bridges of communication across frontlines. In the Yugoslav conflict in the 1990s there was no social media but there were specialised lists, mainly journalists, academics, diplomats and aid workers. In the Ukraine conflict, the role of social media is evident. Much of the population is taking part. To what extent are social media reflecting or influencing the mainstream media? And to what extent do social media therefore reinforce social mistrust, or alternatively maintain or rebuild trust and empathy across divided communities against negative stereotypes?

Knowledge of the local political-socio-economic context in which social media interactions are taking place is critically important in conducting social network analyses. Without such knowledge it is nearly impossible to identify and map key actors (nodes) and their interactions (edges). Recognising patterns of interaction among participants in a social network is extremely important because the trust that is usually developed in the process tends to last longer than the particular event that triggered it in the first place.

There are preliminary indications that on the one hand how the 2014 floods in the Balkans have brought divided communities together in their suffering, facilitated through social media, while on the other hand how responses in the conflict in Ukraine which broke out in 2014 have become more polarised through social media.

X.3.2 Measuring Empathy and Trust

The challenge we face is demonstrating whether social media is reinforcing the mistrust created by the fighting or is helping to bridge the gap between the estranged communities. Sentiment analysis is a notorious challenge in internet data research. Balkans area specialism and language knowledge, combined with International Relations expertise on the one hand, and computer science expertise combined with fortuitous Ukrainian and Russian language and area knowledge, on the other, has facilitated our research planning.

One way into identifying trust and empathy has been to compile a list of terms or hashtags, as potential indicators of positive feelings or inter-ethnic solidarity in Bosnian/Croatian/Serbian. This helps to narrow down the search criteria for data collection which otherwise would be practically unfeasible. Another way is to explore the language communities of social media and whether specific on-line language networks express particular solidarities and are manifested in particular events being the focus of attention, in addition to how they are represented – in particular whether the use of Ukrainian, Russian or English reflects or transcends political affiliations. To analyze this phenomenon quantitatively, we rely on several data mining techniques. On the one hand, we look at the temporal dynamics of Twitter activity during the political crisis in Ukraine and automatically identify various episodes of the conflict during which the volumes of posts diverge in different language communities. On the other hand, we measure the public empathy in response to those episodes by analyzing the sentiment of the posts in English, Ukrainian and Russian speaking Twittersphere. This analysis conducted on the dataset of dozens of millions of social media posts can help us to understand the differences in public perception of the conflict in various language communities, but, also to identify and analyze key triggers (e.g., events, persons) which mobilize public opinion during political crises and social unrests.

Furthermore, through the interdisciplinary research we may identify how apolitical technological tools may have *unintentional political consequences*. For instance, it is known that search and news feed algorithms tend to reinforce people into their divided social media communities, and compound their estrangement (Pariser 2011).

X.4 Social Network Analysis of Sentiment Exchange

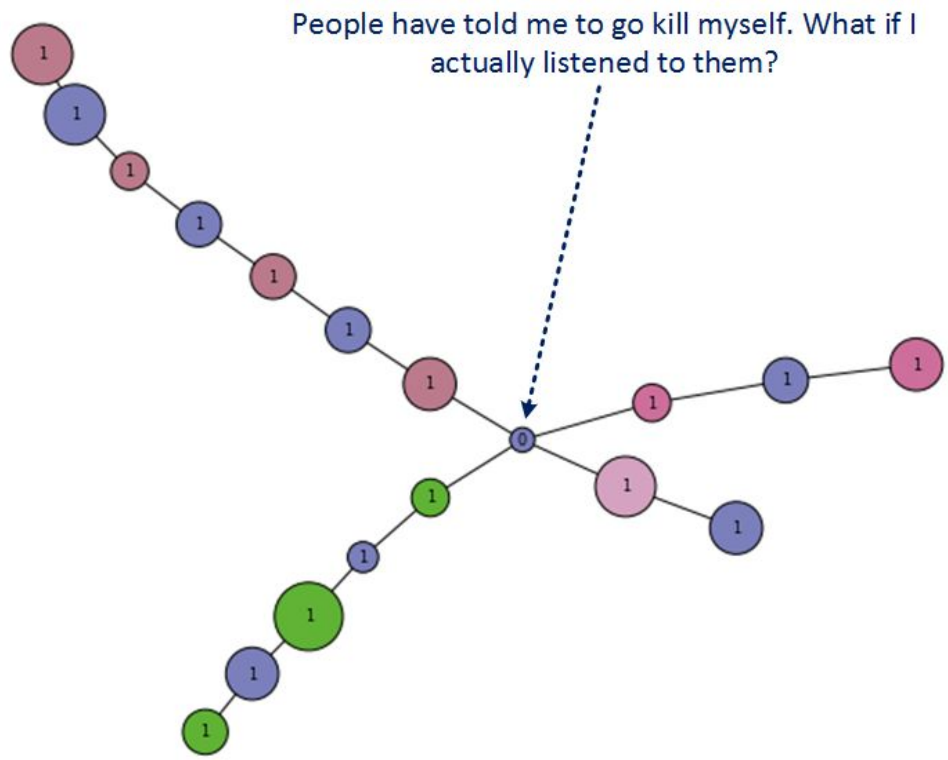
Based on the considerations of the above two collaborative scenarios, in this section we demonstrate how the requirements and needs of social science research can be met with a practical application of social network analysis to study the patterns of empathy propagation in Twitter. We present the *Sentiment Exchange Cascades* - a novel methodology to analyze exchange of sentiments in Twitter conversations - and demonstrate its applicability to analyze the dynamics of social conversation in Twitter for the two different use case scenarios presented in this chapter.

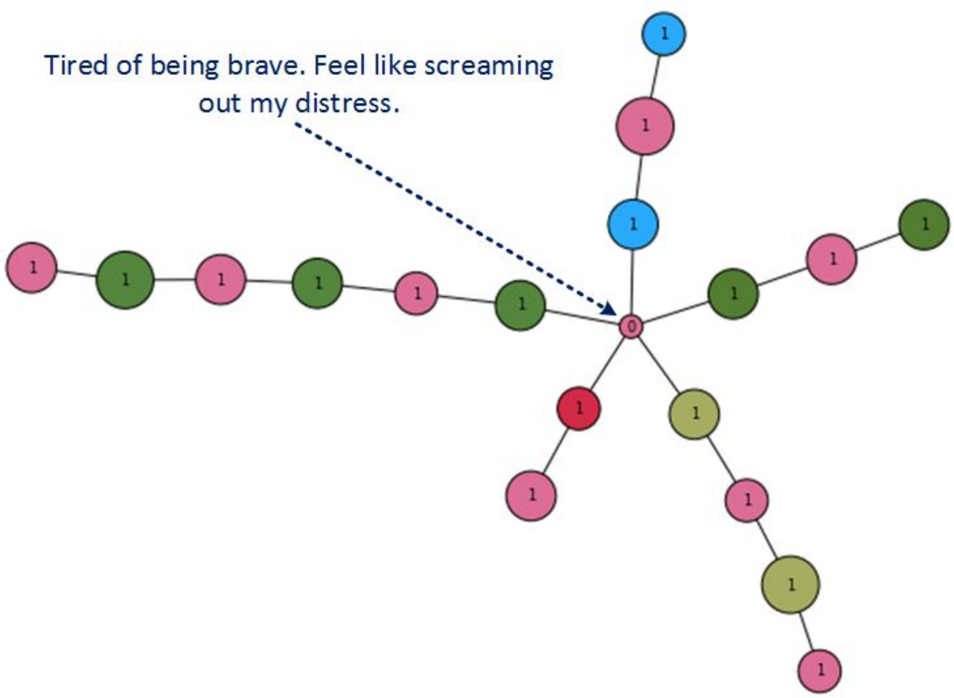
X.4.1 Data Collection

We consider two datasets of tweets for our analysis. The first one was collected during the Euromaidan protests in Ukraine in winter 2013-2014 and is composed of English tweets which contain the #euromaidan hashtag and/or mention Ukraine or the Kyiv city where the main protests took place. The second dataset is collected in fall 2015 for around dozen keywords which indicate depression in Twitter posts and which have been carefully devised by our social scientist partners, e.g., feel + empty, if + kill + myself, not + good + enough, etc. For each tweet in both datasets - which were collected using Twitter streaming API - we also collected threads of reply messages from which we reconstructed the cascades of interactions between individuals (see Figure 1 for example). We have used the following notation to represent the sentiment exchange in cascades of user interactions:

- the node colors represent different Twitter users
- the size of the node represent the sentiment of the tweet as measured by SentiStrength library (Thelwall 2010). Note, that we only considered tweets written in English for this analysis. We also note that SentiStrength provides two scores to separately characterize the extent to which a tweet expresses a positive (POS - an integer score between 0 and 5) and negative sentiment (NEG - an integer score between -5 and 0). For presentation we compute the radius of the nodes with the following formula $R = (5 + NEG + POS)^2$.
- we used integer labels within the nodes to indicate the number of Twitter users mentioned in a post, e.g., a tweet “Glad to meet @userA @userB @userC at this meeting today” mentions 3 different users.

The subsections below show how this novel visualisation of social network interactions allows us to develop a better understanding of what is happening in individual conversations, and is leading to improved understanding from the social science side.


People have told me to go kill myself. What if I actually listened to them?


Tired of being brave. Feel like screaming out my distress.

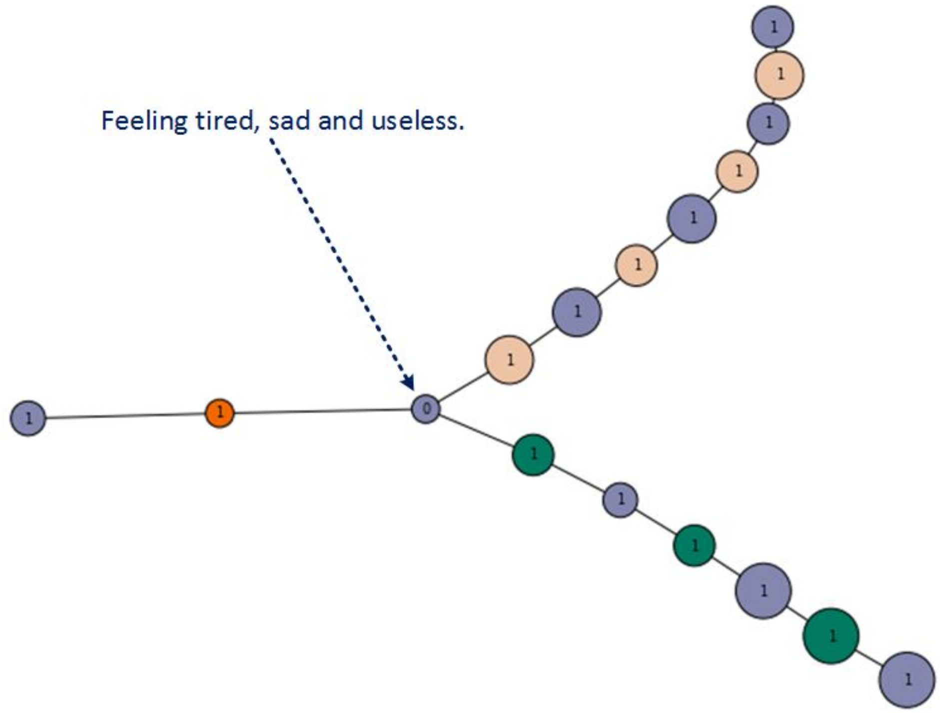


Figure 1. Sentiment Exchange Cascades in response to tweets which express emotional distress: The title of each figure is indicative of the words of the original tweet[3]. Each node represents a tweet and an edge is drawn between two tweets if one is a reply to the other. Each individual user is represented by a different colour. At the centre is the original poster (pointed by the dotted arrow). Each reply thread originating from the first post is shown distinctly. The size of each node is proportional to the positiveness of the sentiment. The number in each node represents the number of people involved in the reply. Note how the sentiment of both the original posters and reposters becomes more and more positive as the reply threads evolve. Further, most tweets involve just two parties, and represent a more intimate conversation than seen in other scenarios (e.g., see Figure 2).

X.4.2 Friends in Need are Friends Indeed: Effect of Social Network Interactions on Twitter Users in Emotional Distress

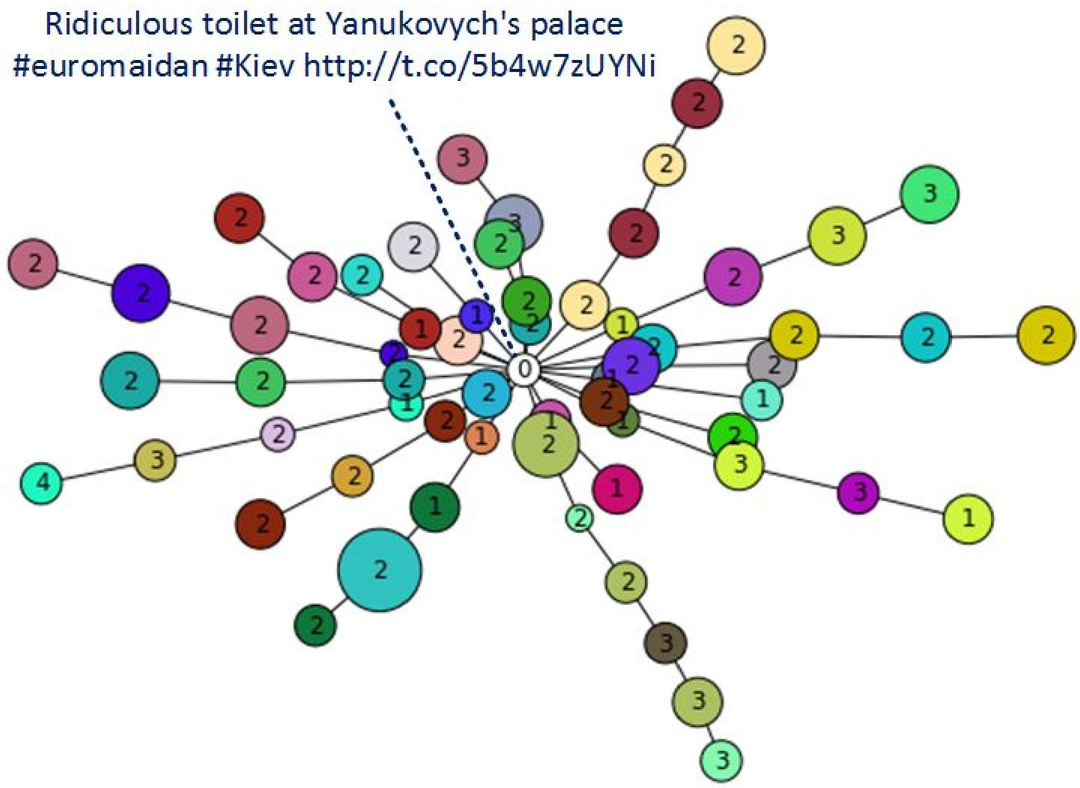
In Figure 1 we present several example cascades constructed from the first dataset of depression-related tweets. The original tweets in the center of each cascade express emotional distress and, so, have very negative sentiment (i.e., small radius). However, the positive sentiment tends to increase as the discussion deviate further from the original tweet. As indicated by the tweets with larger radius (and so a more

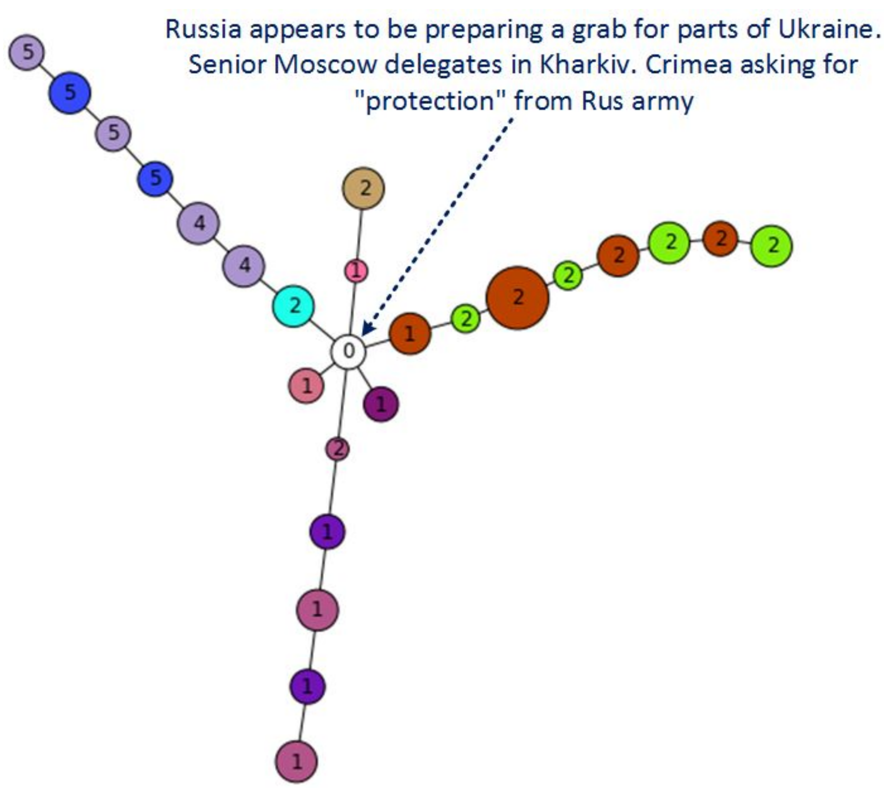
[3] This has been obfuscated, in accordance with ethical practice (Markham 2012), given that users may have placed the tweet in the public sphere but the tweet itself may or may not have been intended for public consumption.

positive sentiment) located just next to central nodes, Twitter users try to “cheer up” their fellow Twitter users, e.g., “you’ll be ok!”, “you are beautiful with an amazing twitter personality”, “life needs you!”, “sending you some love and support”, “stay strong”, etc. More interestingly we also observe that the sentiment of consecutive tweets from the author of the original tweet (i.e., the tweets with the same color as the original tweet) is also amplified throughout the discussion suggesting, that this “social therapy” yields positive results: the user in need starts posting more positive tweets typically expressing thankfulness, e.g., “thanks”, “I love you babe, thanks”, etc.

X.4.3 One-to-One Conversation vs Group Discussions

Next we consider several sentiment exchange cascades for the tweets from the Ukraine protests (Figure 2). We observe several distinguishing features in comparison to our analysis of emotional distress in the previous section. We notice that the conversations with the longest cascades are mainly initiated by the famous figures, e.g., politicians, journalists or celebrities, who often do not follow-up on replies from their followers. This is indicated by an observation that a single central node is colored in white color. Nevertheless, we observe long threads of conversations among the original Twitter user’s followers. More interestingly, we observe that many discussions tend to engage multiple users (up to 5 as indicated by the number of users mentioned in the tweet within the node. The very nature of Twitter, with its small character limit for each tweet, limits the number of users who can be mentioned in any tweet.). This is in contrast to the results from the previous sections where all threads of cascades are predominantly one-to-one conversations (i.e., all nodes have a label “1” indicating a single person is mentioned in each tweet).


Ridiculous toilet at Yanukovych's palace
#euromaidan #Kiev http://t.co/5b4w7zUYNi


Russia appears to be preparing a grab for parts of Ukraine.
Senior Moscow delegates in Kharkiv. Crimea asking for
"protection" from Rus army

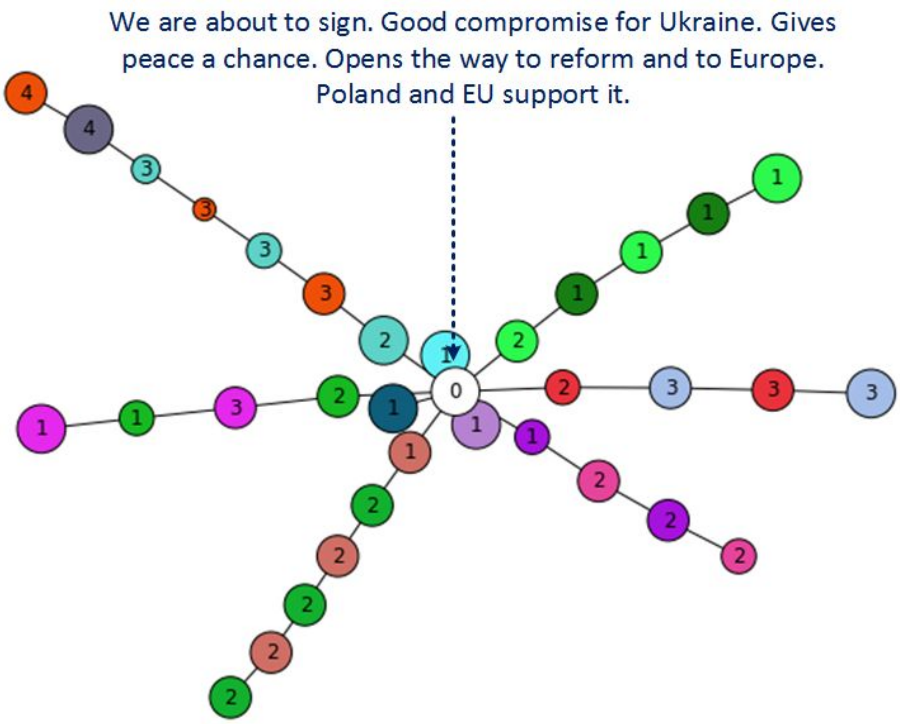


Figure 2. Sentiment Exchange Cascades for Euromaidan tweets: The visualisation scheme is similar to Figure 1.

As far as the sentiment is concerned, politics-related discussions have a much more nuanced nature. In many cases, the sentiment of individual users do not change. For instance, we notice that information propagation threads of the discussion predominantly feature neutral sentiment across the majority of tweets in the discussion. In other cases, the sentiment of users increases, sometimes of both of the parties involved in a reply thread. When we examine the threads themselves, however, we find many instances with jingoistic discussions with a vivid confrontation pattern, that tend to have much more polarized sentiments throughout the conversation thread. Looking through individual tweets, we also observed a difference between the very confrontational discussions - which were predominantly attributed to one-to-one discussions between two opposing sides - and more open minded discussions between large number (up to 5) of participants.

Overall, we believe that the cascades of sentiment exchange presented in this section can prove to be a useful tool in interdisciplinary analysis of dynamics of interactions between users in social networks. This technique can facilitate the inter-disciplinary approaches discussed in the earlier sections in two respects. On the one hand, with this approach we aimed to build a visualization tool for social scientists to be able to "zoom in" within the large datasets of tweets and analyze the patterns of sentiment exchange within small, individual, conversations that are so crucial to obtain insights in the social sciences. On the other hand, we aimed to leverage on the idea of sentiment cascades to study the emerging patterns from sentiment exchange on a significantly larger scale, i.e., in conversations among millions of individuals.

X.5 Meta Discussion on the Nature of Collaboration between Computer and Social Sciences

Having reported on the two collaborative efforts we are undertaking, and how social network analysis has allowed us to easily draw new nuggets of insight from the vast mountain of data facing us: we conclude by discussing two meta questions about the broader nature of our collaboration across disciplines, which have been vexing us. The first is motivated by a respect for the rights of those whom we study. Haunting all of the above are crucial questions about the ethics of trawling Twitter to extract data on emotional distress or other extreme situations and what we then do with these data. How may we attach meaning to data, in such a context? The second question is more reflexive: are we doing transdisciplinary research? This is not merely a navel-gazing query, but rather a yardstick to measure our collaboration against and to ensure we remain reflexive about the nature of our joint working.

X.5.1 Attaching meaning to data and attendant ethical concerns

X.5.1.1 Being lost or found in big data

In the Emotional Distress study by using word search terms rather than hashtags, we seek Twitter users who are using the platform in a way that is arguably less public and more ephemeral, and whose expectations for privacy are likely to be different (and greater). By making ephemeral - if not private - data public through research, we potentially spotlight these users, and could risk revealing highly sensitive personal information.

Leaving aside well-rehearsed arguments about whether or not Twitter data are technically public, disciplinary differences in how we come to visualise such data are important. For those working quantitatively, all cases are anonymised or blurred; no one case is visible. When we begin to analyse Twitter qualitatively, we surface or spotlight cases that up until then had been invisible. Regardless of whether this is quantitative or qualitative analysis, extracting Twitter information and turning it into data, and creating new databases of tweets through archiving of research data, raises a number of serious ethical questions which up to this point have been dealt with through specific disciplinary approaches. Over and above the issue of archiving, there are also important ethical questions to ask about using data for analysis. There are ways to mitigate the risks of using data qualitatively, including what Markham (Markham 2012) calls “fabrication as an ethical practice”, or thematic analysis that refrains from using quotes. Our choices in the presentation of data for analysis mean acknowledging, if not completely reconciling, different disciplinary perspectives on ethics.

X.5.1.2 Systems approaches facilitating interdisciplinary research

One potential solution to the above, and a potential bridge between computer and social scientists working on this project is provided by systems approaches, which have influenced key International Relations theorists such as Kenneth Waltz (1979) or the peace theorists Johan Galtung (1996) and Anatol Rapoport (1974).

Systems thinking spans the social and natural sciences because of the inclusive and non-anthropomorphic notion of a system, and can be very useful here in facilitating the integration of different facets of knowledge coming from different disciplines – in this case, International Relations and Computer Science, or Sociology and Computer Science. Systems thinking as a general framework for observing and explaining the world is particularly useful in dealing with the complex interface between human/social and technological phenomena such as social media. Indeed, the concept of resilience, now central to international disaster, development and security management, originates from systems thinking. Technologies, such as the Internet, have likewise challenged sociologists to rethink how they conceptualise and research the social (see, for instance, Castell's (2010) work on the global network society and Law and Hassard (1999) on actor network theory (ANT)). Such theories, like the systems approach within International Relations, raises questions of what should be included in analysis of the social and at what level(s) this analysis should take place. Actor network theory, for instance, proposes that non-human actors should be included in understandings of the social.

What significance may we attach to what people say on Twitter or other social media? How do social media interactions relate to offline interactions? How consistent are people's online activities with their offline lives? The virtual world and the patterns of the virtual world have their reality, but they are not all of reality. The situations of conflict or disaster involving the risk of death, injury or physical loss as well as expressions of suicidal intent on social media starkly surface the relationship between the virtual and offline worlds.

The systems approach, as a way of coordinating or integrating research efforts of multiple researchers coming from different disciplines, is aimed at building common frames of understanding the natural and social reality. Generally, it involves using a system as the basic unit of analysis. The hope is that this ontological assumption can address the duality of natural and social worlds, which often stifles fruitful interdisciplinary collaboration. In the context of our analysis of Twitter responses to the 2014 floods in the Balkans and the Ukraine conflict, this approach is intended to allow us to see regularities and patterns in the seeming deluge of millions of Tweets. Our particular concern has been to find out whether political communities transcending and blurring the existing boundaries of social and political interaction in the Western Balkans and Ukraine are emerging from this deluge. There is a reason to believe, for instance, that the trust and empathy triggered by the 2014 floods may last beyond the disaster and increase the resilience of the affected communities faced with similar disaster situations in the future.

We need to consider the relation between individual and aggregate data, and how to reconcile the principle of methodological individualism with emerging patterns at the aggregate level. While individual tweets can be attributed to individual Twitter users, the patterned tweets do not constitute per se a conscious collective entity or conscious collective action, even if the patterns of social interaction have social consequences. While social media offers new powers of communication between individuals by-passing official institutions or traditional media, big data analysis may be inclined to see human behaviour as following conditioned social behaviours, and minimise the possibility of individual agency and freedom. Here we return to the question of the human as against the system and to what we earlier referred to as the need to hold on to small data within the big.

X.5.2. Learning through Doing: the nature of social and computer science collaboration

As noted in the introduction, the broader project that our study is a part of was set up as a transdisciplinary one and could be seen to fit in with a general move towards harnessing research to solve problems outside the university for instance for government or industry - a move that could lead to a blurring, if not the dissolution, of disciplinary distinctions and autonomy (Krishnan 2009a). It is an open question whether what we are doing is multi-, inter-, cross- or transdisciplinary research. If the key distinction between these practices rests on whether or not disciplinarity disappears then we would seem to fall short of genuine transdisciplinarity. Moreover transdisciplinarity is associated with a much longer process of planning at the research design and initial management stage than a sandpit process facilitates (Hollaender et al 2008, 387). Perhaps more important than the label, however, is what we learn through doing. Like the reaction of the family in the children's book 'Going on a Bear Hunt' (Rosen and Oxenbury 1989) when they encounter obstacles like mud: 'we can't go over it. We can't go under it. Oh no! We've got to go through it!'. The computer and social scientists involved in this project are finding out what it means to work together as computer and social scientists through 'going through it', and it is this process we have illustrated through the two projects outlined in this chapter. In thinking across these two projects more interesting question than whether or not we are doing transdisciplinary work might be what we believe is being blurred through the process of crossing disciplinary boundaries. What, as (Krishnan 2009b), suggests, do we hold to be true about our own discipline?

Working with our computer (respectively, social) science colleagues has been as revealing of ourselves, what we do and believe as sociologists or political and computer scientists, as it has about the nature of other disciplines and our relationship to them. Through this work we are grappling with the fundamental questions about the distinctiveness of the sciences and the humanities. Those who champion this process of grappling and who are wary of philosophies claiming absolute knowledge about humanity might turn out to be our most useful guides in this 'journey':

To bring men to liberty means to bring them to converse with one another. Mere opinion melts away in favour of well-founded judgement in the loving struggle with one's neighbours (Jaspers, 1953, p. 154).

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