# **The Academic Organisation of Data Science**

Around ten to fifteen years ago so called E-Science institutes starting popping up all over the world, as developing computational methods was high on the research calendar in academia. At the time, these institutes were started to “understand digital devices [and develop] conceptual framings and innovative methods for analysing their effects” (Ruppert, Law & Savage, 2013, p. 29). Today, most of these E-Science institutes do not exist anymore; they have been replaced, it seems, by Data Science institutes (DSIs) – sometimes called centres or initiatives – of which there are now roughly 40. All of these DSIs except for one have come into existence between January 2013 and December 2015. In addition, there are now about 120 postgraduate degrees related to terms like Data Science, business intelligence, or advanced analytics around. “Data Science,” and the related “Big Data” surface more and more; academic journals like “Big Data & Society” are now publishing articles about the Big Data phenomenon. But what do Big Data and Data Science refer to? What do these terms mean? And how do these phenomena impact on the organisation of academia?   
 In order to answer these questions we study the academic organisation of Data Science to find out how academia has responded to (industrial) Big Data practices. We do this more specifically by focusing on four topics, which we describe shortly. First, however, the question is what is Big Data and what is Data Science? Big Data is generally seen as referring to the huge data sets that are now coming into the possession of companies and universities, sets of data which are so big they are changing the ways in which research is done. Big Data is a phenomenon which is both scholarly, technological and cultural, resting on “the interplay of technology, analysis and mythology” (Boyd & Crawford, p. 663). It is a phrase which “seems to have mysteriously emerged from nowhere over the last couple of years and now it commonly appears in newspaper headlines, the pronouncements of politicians, and the promises made by marketing groups” (Warwick, p. 1). As Fairfield and Shtein argue, “Big Data […] is big news” (2014, p. 38). According to Boyd & Crawford, 2012, “The era of Big Data is underway. Computer scientists, physicists, economists, mathematicians, political scientists, bio-informaticists, sociologists, and other scholars are clamouring for access to the massive quantities of information produced” (p. 663).   
 Data Science is defined by Waller & Fawcett as “the application of quantitative and qualitative methods to solve relevant problems and predict outcomes” (Waller & Fawcett, 2013, p. 78) especially with regards to Big Data. Data Science can thus be seen as the academic response to the Big Data phenomenon – although one could also argue that Data Science is similar to Big Data but simply happening in a more academic setting. In a leaflet written to promote Imperial College London’s Data Science Institute, it is written that Data Science is “an essential element of all modern interdisciplinary scientific activities” (p. 3) and that “Data Science is not only concerned with the tools and methods to obtain, manage and analyse data, it is also about extracting value from data and translating it from asset to insight” (p. 3). Data Science, in short, is seen (by some at least) as the future of academia, the latest academic fashion craze.   
 Data Science is very difficult to discuss or comprehend as it makes use of methods from many different disciplines all situated “within the broad areas of mathematics, statistics, and information technology” (Diggle, 2015, p. 794). Data Science consists in this view of statistics *and* informatics, which refers to the technology, software and hardware needed (the infrastructure) to convert huge amounts of data into usable formats (Diggle, p. 794). The organisational problem with statistics is that it is a discipline with relations to multiple other disciplines but is usually put together with mathematics in terms of research departments. In Diggle’s opinion universities need to have statistics institutes in order for academics to work together there *and* within a university department. The DSIs which are coming into existence might achieve this goal as well, or so Diggle argues: “Deep involvement of statisticians within the burgeoning number of Data Science institutes might be a more effective tactic to achieve the same goal, at least in the short term” (p. 806). Collaboration is especially important for a discipline like statistics, as the unique selling point of this discipline is that it can be relevant “to the whole of the natural and social sciences” (p. 807). Data Science, and specifically mathematics and statistics should in Diggle’s view work together “when making the case for the fundamental importance of the mathematical sciences to the future health and wealth of UK society” (805).   
 Data Science is different from former ways of analysing data in that the data nowadays is more heterogeneous and unstructured, “emanating from networks with complex relationships among its entities” (Dhar, 2012, p. 2). In order to understand this kind of data, collaboration is needed, as different academic fields all have their own particular skill set which is argued to be not enough in itself to deal with Big Data: “From an engineering standpoint, it turns out that scale matters in that it has rendered the traditional database models somewhat inadequate for knowledge discovery” (Dhar, 2012, p. 3). This is the problem with being a data scientist. There are no individuals “that can possibly have all of what is needed by a data scientist” (Waller & Fawcett, 2013, p. 78). This is also partly why there are so many Data Science Institutes all around the world: to deal with the fact that new opportunities of data collection require new models and methods and collaboration.

# **Research Interests**

Since it is estimated that “90% of the data in the world today has been created in the last two years alone and the world’s data will grow by 50 times in the next 10 years” (Technische Universiteit Eindhoven, Web) it is not surprising that DSIs are formed and are replacing E-Science institutes. It is also not very astonishing that social scientists are now writing about Data Science, business analytics and topics like algorithms, as academics are realising that (big) data might become *the* power of the 21st century. Data Science is thus high on the research agenda, but how do these institutes actually work? And what kinds of data do they work with? Some of the topics that we are interested in discussing by presenting an overview of these institutes are: (1) the different definitions of Data Science as presented by these institutes; (2) the goals of these institutes in terms of output and collaborations; (3) the relations to both existing and emerging academic disciplines and (4) relations to other worlds, like civil society and industrial Big Data practices. By focusing on these four topics, we can look at how new forms of knowledge are (allegedly) being created within the DSIs we discuss and how academic organisation is affected by the Big Data phenomenon. The question we then aim to answer with theses research efforts is the following, as we ask: how does the Big Data phenomenon have an impact on the organisation of academia?

# **Methodology**

One field which has paid attention to the organisation of scientific work since the late 1970s, is STS, a discipline which has “added significantly to our understanding of science” (Roth & McGinn, 1998, p. 216). In particular, STSers have been publishing about practice oriented laboratory ethnographies, controversy studies, and historical portraits of science. Nowadays, STSers “take for granted that an understanding of scientific *knowledge* requires a thick engagement with scientific *practice*” (Mody, 2015, p. 1). We propose to study Data Science institutes by looking at scientific practices and infrastructures from an STS perspective. STS literature focusing on knowledge production could prove valuable for discussing today’s scientific infrastructures in terms of how academia is organised, what the goals are of the Data Science institutes, who is involved, and what the relations are between the DSIs and industry and civil society. It could be argued for example that knowledge has moved from the meticulous work in the laboratory to (online) Big Data communities.  
 There is a lot of literature in STS on the training of scientists (Roth & McGinn, 1988; Kohler, 1987). These studies show how “pedagogical institutions can mirror and drive wider cultural change” (Hackett, Amsterdamska, Lynch & Wajcman, 2008, p. 378). With the commercialisation (and arguably de-commercialisation) of science, this topic has never been more relevant than today, as relations between consumers and producers of knowledge are renegotiated with the emergence of DSIs, some of which aim to restructure relationships between academia and industry, and the whole assemblage of how science is organised. One particular STS journal in which many relevant literature is published on both scientific practices and the training of scientists is Big Data & Society. Texts from this journal will especially prove insightful when discussing the nature of the DSIs around the world.   
 In order to expand this project we invite collaboration from researchers from other universities. We do this by making both a Google Map and a Google Spreadsheet[[1]](#footnote-1) containing key information about the DSIs which are publicly accessible and everyone can comment on. This way, we hope to get other academics, not necessarily social scientists, involved in this project as we believe this could lead to more information with regards to the different DSIs worldwide. At this point in time, the map simply presents and overview of where these institutes are, while the spreadsheet contains information, which could provide the basis for a comparison, on the following: the locations of the DSIs; the degrees offered by the universities linked to these institutes; the starting dates of the institutes; information regarding funding and the relationship between the institutes and industry; a list in terms of academic disciplines of who are collaborating in the institutes, how many people are involved and who these people are. In the following we start to compare key themes that surface when studying the information presented by the DSIs by incorporating STS literature and reflecting on our own experiences in working in the DSI at Lancaster University.

# **Preliminary Findings**

As mentioned before, our main goal for this project is to find out how the Big Data phenomenon has an impact on the organisation of academia. We start by discussing the different definitions of Data Science as presented by the DSIs on their respective websites. When looking at these websites there are always short lists with bullet points about certain goals and aspirations, yet there are hardly any DSIs which actually explain what Data Science is (in their view). They all talk about Data Science and say what they aim to achieve, or who is involved in the centre or institute, but they hardly discuss what Data Science is. Why? Is it perhaps because as a term it is as ungraspable or opaque as Big Data? Take this descriptions for example, copied from the websites of the DSIs in Manchester and Michigan:

“Manchester's Data Science Institute acts as an access point to the University’s expertise in data science, facilitates interactions between data science researchers and problem holders, owns the University’s data science strategy, and will deliver sustainable support for the community (Manchester, Web).

“Data science is now widely accepted as the fourth mode of scientific discovery, on par with theory, physical experimentation and computational analysis. Techniques based on Big Data are showing promise not only in scientific research, but also in education, health, policy, and business” (Michigan, Web).

Both of these descriptions illustrate that Data Science is now generally accepted as a way of creating knowledge and that there are researchers ‘doing Data Science’. Yet there is hardly any information on how these institutes work or aim to work, or with which data, or even what Data Science is. This lack of clarity can be explained by the fact that most DSIs are only just beginning to surface and they lack clear definitions and there are hardly any projects within these DSIs which are finished. It seems almost as though these institutes are starting to pop up more and more as reactions to each other, or perhaps to what happens in industry, without the institutes themselves having a clear idea of what needs to be done in the fields related to Data Science, which arguably are all academic fields.   
 Of course, there are exceptions. In Dundee, where the first DSI was founded already in 2011, two years before the second DSI sprang to life, there are academics with a clear idea of how Data Science should be tackled. Even though the following description still does not explain what Data Science is or should be like, it does at least give an indication of what a data scientist is and what kinds of data they work with:

“There has been a recent upsurge of commercial interest in both Business Intelligence (BI) and Data Science (DS). […] BI is about extracting useful information from a mass of raw data.  A large number of systems, techniques and processes can all be involved in doing [this.] DS has much in common with BI but Data Scientists tends to work more with ‘big data’ and have a greater focus on developing custom algorithms and visualizations.  One good definition of a Data Scientist is that they know more statistics than a programmer and more about programming than a statistician.  The term data scientist doesn’t imply that scientific data is involved, although it certainly can be; most data scientists work on commercial data” (Dundee, Web).

The differences between some of the terms used in the DSIs never really become clear though. In Dundee, business intelligence is mentioned, in other parts of the world the word “analytics” is often used in relation to both Big Data, Data Science and Business, but what Data Science entails is never entirely clear. Most DSIs have a description on their website of what their goals are but even these are not completely transparent. As far as we could distinguish, there are only a few DSIs which actually define Data Science. One of these definitions is given by Boston University, and this still does not say much, as Data Science is defined as “the methodical extraction of knowledge from data” (Web). Two more descriptions are presented by the Universities of Massachusetts and Rochester respectively: “Data Science develops methods to collect and analyze large-scale data, and uses them to make discoveries and decisions” (Massachusetts, Web); “Data science is the creation and application of powerful new methods to collect, curate, analyze, and make discoveries from large-scale data” (Rochester, Web). These last two descriptions are somewhat more detailed than the extraction of knowledge from data as Data Science is defined in Boston, but there still is no clarity as to how this actually works. The question is, with about 40 institutes around the world all working on Data Science, whether they do not define the topic of their research because they (A) do not know themselves what Data Science precisely is, or (B) assume that everyone who reads their websites knows what Data Science is.  
 The second question we are interested in is what the goals of the DSIs are in terms of output, like publications, degrees, and collaborations. There are two main goals which come back most often when looking at the different lists of bullet points or explanations presented by the DSIs as to their goals. First of all, as Leonelli (2014) argues, “the novelty of Big Data science lies in (1) the prominence and status acquired by data as scientific commodity and recognised output both within and beyond the sciences and (p. 2) the methods, infrastructures, technologies and skills developed to handle […] data” (p. 2). Most DSIs state that the main purpose of the DSI is to get scientists together from different disciplines to collectively develop frameworks and methods to deal with Big Data. Leonelli is right when she argues that data is seen as a commodity and DSIs are working on methods to delve this commodity. This goal can be described as aiming to do “world-leading research” (Warwick, Web) or “synergis[e] different fields of expertise” (Delft, Web). In Edinburgh, the DSI “acts as a hub for national and international data across the arts and sciences; developing networks of expertise in managing and accessing all forms of data” (Web). The point is clear: collaboration is high on the research agenda, as together academics can work on methods to analyse big amounts of data.   
 Next to this, there are those who write about teaching and training data scientists. In Bournemouth, the first goal listed is to create a platform for “interdisciplinary training of highly skilled and internationally excellent researchers and leaders in the Data Science area covering big data, advanced/predictive analytics, data intensive computing and their innovative business, engineering and science applications, in a cross-disciplinary environment” (Web). The mission in Virginia meanwhile is “to achieve recognized excellence in research and education in the interdisciplinary field of data science” (Web) and at Columbia the DSI is “training the next generation of data scientists and developing innovative technology to serve society” (Web). It is perhaps surprising that there is only one institute which actually mentions (research) ethics with regards to the collection of big amounts of data.   
 There is a third goal which is important, we would argue, but this does not come up as often on the DSIs websites. An exception is the University of Essex’s DSI, where there is research into the “ethical, legal and human rights aspects of data” (Web) which is a very important side to Data Science. We would argue that as the amounts of data which are available are increasing and having an impact on research methods, the question of how we deal with this in terms of values and ethics is an important one. This is thus concerned with studying what the consequences are of the availability of big amounts of data for academia and industry. Related to this, there is an article in Big Data & Society by Kitchin (2014) who writes that because of the availability of big data we are now arguably moving into a fourth paradigm of science. After experimental science, theoretical science, and computational science there is now exploratory science which is “data-intensive; statistical exploration and data mining” (p. 3). The question raised at the University of Essex, about the ethical aspects of data, is therefore a vital one, as the question is how do we make use data as academics and what values do we try to uphold when constructing knowledge?  
 The third question we are interested in discussion is concerned with the relations of DSIs to both existing and emerging academic disciplines, as we wonder: who are collaborating in the DSIs? Thinking about the disciplines which are involved in the different DSIs is very important, as studying which disciplines are represented in DSIs and are doing Data Science can lead to new views on existing and emerging disciplines and changes in epistemologies. As Kitchin (2014) argues, “there is little doubt that the development of Big Data and new data analytics offers the possibility of reframing the epistemology of science, social science and humanities, and such a reframing is already actively taking place across disciplines” (p. 10). We already gave a few examples of the disciplines involved, and the goals for collaboration, but not explained really in broad lines who is involved in most of the DSIs.   
 As Big Data and Data Science can be about almost any topic, there are many differences in the kinds of disciplines involved, based on the foci of the universities. In general, there are almost always computer scientists, mathematicians, and statisticians working in the DSIs, while engineers are also very common. Of course this can be explained. In Lancaster for example health and environmental issues are high on the research agenda. Therefore, it is logical that Data Science practices in Lancaster focus on developing methods and frameworks for the natural environment. Collaborations in the different DSIs are really about combining the disciplines strongly represented at universities. In Chicago for instance, the DSI is a collaboration between policy experts and computer scientists who are trying to create “computational and data-driven solutions to large-scale social problems in areas such as healthcare, education, sustainability, and community development” (Web).  
 The final question is how academic practices relate to industry. As Beer & Burrows (2013) argue: “digital data inundation is not just a narrow technical methodological matter for the social sciences; it has been argued that it has far broader implications for disciplinary jurisdiction, the relationship between the academy, commerce and the state, and, indeed, for the very nature of the sociological imagination” (p. 47-48). But how does this work out in reality? What are relations like between commerce and academia and the state? There are big dissimilarities between the different DSIs. Some DSIs have for example grown out of collaborations between academia and industry, like Imperial College London’s institute. Other centres do not mention any industry partners, some of which state that they are interested in working with industry and some of which actually already do so but refrain from naming companies.   
 Even though these are preliminary findings, it is clear that it is unclear what Data Science is and what the DSIs are doing. The first question we tried to answer was concerned with the different definitions of Data Science as presented by the DSIs on their websites. Only three out of forty institutes actually define Data Science but even then the description of what Data Science is, is very general. There are all these institutes and they all argue we should develop methods and frameworks, train data scientists, and collaborate university wide to deal with the Big Data phenomenon. But it is never precisely clear how it is suggested this is or can be done. This also answered the second question, which was what the goals of these institutes were. The DSIs discussed all have collaborations in mind with industry and in ways in which different disciplines can come together to create methods to critically assess big data sets which are now becoming more widely available. It is just not clear how. In terms of disciplines, most institutes employ computer scientists, mathematicians, statisticians and engineers, whilst in some cases social scientists and even communication specialists and health researchers are participating in DSIs, depending on the expertise of the respective universities. Lastly, we briefly mentioned relations to industry, although this is an area more research would be beneficial on, as there is hardly any information available regarding the ways in which DSIs and industrial partners work together. This is mainly because most of the DSIs have only just started to surface.   
 Finally, as we come from a more social science background, we are of course interested in how social science methodologies change or are affected by the Big Data phenomenon, and we would like to discuss in more detail the relations between Big Data, Data Science and sociology, both in Lancaster, where we are affiliated with the DSI, and elsewhere. For now, it seems, as Mützel (2015) argued in Big Data & Society that “projects using Big Data, from data journalism to computational social science, have little engagement with sociology, although many sociological insights could strengthen analyses; in turn, sociologists could benefit from enhanced computing and visualisation skills” (p. 3). The question is whether this is really the case and what the role is of social scientists in DSIs. As Mützel also argues, “sociology has much to contribute to the new arenas of social science research: because of its insights and techniques to study meaning and how the social is structured, sociology makes itself very relevant to data science projects mining large data sets” (p. 3). But how does this work out in reality? Are there many sociologists partaking in DSIs? Or are DSIs, as our preliminary findings suggest, mainly institutes where more quantitative sciences come together?

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1. The Google Map can be found here: <https://www.google.com/maps/d/viewer?hl=nl&authuser=0&mid=z8wOvDZaZCBY.krf0RpgiiqSU>   
   The Google Spreadsheet link: <https://docs.google.com/spreadsheets/d/1lsQNEhHtKV5JC9Q65ZmYIVhFjfgAz34hvORPDkFQdoY/edit?pli=1#gid=0&vpid=A1> [↑](#footnote-ref-1)