The Mathematical Media Room

1 Purpose and Aims

The aim of our programme is to develop a framework that reduces the gap between academic research and the media, so that research can offer rapid insights into evolving social phenomena. The project starts from the premise that the gap between academic research and currently emerging genres of knowledge production, such as data journalism, is too wide, especially considering the ever-shorter time scale on which societal and cultural transformations are taking place.

The present socio-cultural climate is characterised by the increased influence of viral and algorithmic logics. The 2016 presidential election in the USA brought the term 'fake news' to prominence, the question being about the scale and effectiveness of false news stories in influencing voters (Allcott & Gentzkow, 2017). This follows on from worries about the dangers of 'filter bubbles', where the suggestion is that algorithms limit the amount of information citizens have access to, leaving them to hear self-confirming views (Pariser, 2011). The attempt by company Cambridge Analytica to build a political personality algorithm brings up similar issues: Can social media platforms such as Facebook be used to manipulate citizens on an individual level?

In addition to questions about our online privacy and interactions, we are also living through massive demographic changes in our society and changes in our culture and values. Segregation down ethnic and social lines are increasing, as is financial inequality. There has been a rise of extreme right-wing views across Europe and the US, and it occurs against a backdrop of a change in how society thinks about racial and sexual discrimination.

These are all phenomena that impact our society, and they should be investigated with academic rigour. But in this era of ever-shorter news cycles, it is often not the university researchers who are providing the immediate insight. Instead, it is often faster-responding actors such as bloggers and data journalists who are the first to analyse the data, propose explanations, and discuss the consequences. Academics typically respond much later to the current challenges in society.

This disconnect between academia and the media is particularly disappointing, since many of the ideas around the spread of information in social groups and societal change have already been studied by academics. There exist solid theoretical frameworks, statistical tools, and mathematical models for tackling these problems. It is the aim of this research programme to amend the gulf in timescale and methodology between how applied mathematicians and social scientists work on problems, and how data journalists and online bloggers work. We live in a world where theories and ideas are proposed in newspapers and on blogs, to become rapidly and widely spread on social media and discussed on online forums. The immediate availability of data, wide-availability of computational tools, and established theories in the social sciences means that academics should be able to respond rapidly to the challenges posed by society. Indeed, data journalists and bloggers have proved that they can rise to this challenge, why can't academics do the same?

The programme brings together expertise from applied mathematics, sociology, and journalism in developing a research framework that combines mathematical models, well-established social science methods and open communication with the general public. In this research programme we aim to draw on applied mathematics in developing ready-to-use social science tools that can reduce the gap between academia and the media. We will:

1. Develop a capacity, in the form of what we call a *Mathematical Media Room* — a set of analytical tools for both data analysis and explanatory modelling of social phenomena, both online and in real life.
2. Apply these tools to pressing current social problems, publishing the results both as open access scientific reports and as part of journalistic articles in leading media outlets.

3. Research the challenges that must be overcome in order to make academia more responsive and determine guidelines for rigorous data journalism.

The programme is a collaboration between David Sumpter (Professor of Applied Mathematics, Uppsala University, See http://www.david-sumpter.com), Simon Lindgren (Professor of Sociology, Umeå University, See http://www.simonlindgren.com) and Torill Kornfeldt (Freelance Journalist, see http://www.kornfeldt.se), as well as two leading international data journalists Monica Ulmanu (The Guardian/The Washington Post, see https://monicaulma.nu) and John Burn-Murdoch (The Financial Times, see https://www.ft.com/john-burn-murdoch). In addition to these co-applicants, Alex Szorkovszky, a postdoc in mathematics at Uppsala University concentrating on explanatory models will also work in the programme. In addition to these participants, the following will be appointed:

1. One PhD student. Joinly supervised by Sumpter and Lindgren, and working with Kornfeldt.
2. One postdoc based in Umeå in computational social science concentrating on explanatory models.
3. One postdoc based in Uppsala concentrating on statistical models and visualisation.

2 State of the Art: The Academic/Journalistic Gap

The academic analysis of emergent and ongoing societal transformations often happens on a much slower time scale than in increasingly popular genres of knowledge production such as citizen journalism, data journalism, and other forms of online publishing. It takes many years to complete a research project; standard practices require aligning with time-consuming processes of peer review, conference presentations, or book proposals. This means that when academics finally respond to a pressing issue, the general public who originated the problem have often moved on to something else. Even though there is an increasing number of exceptions to this rule, with studies of fake news (Allcott & Gentzkow, 2017; Vosoughi et al. 2018) and filter bubbles (Del Vicario et al., 2016; Bakshy et al., 2015), the overall situation can still be vastly improved, especially in European research.

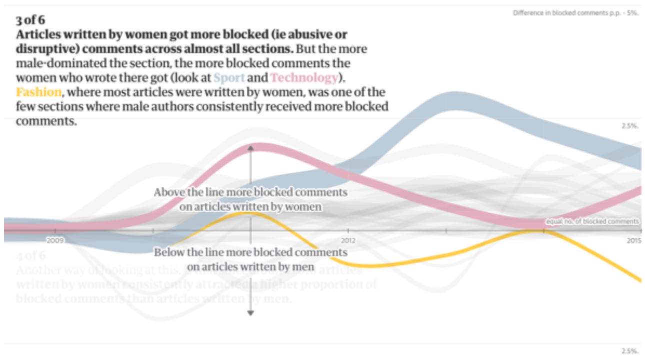

***Figure* 1*. Visualisation of the Guardian comments section. Monica Ulmanu organised over 70 million entries and used the data to drive a story about how articles written by men and women were commented on differently.*

Data journalism has the ability to very quickly shape the public understanding of current events. A prominent example of this is the website FiveThirtyEight, owned by media conglomerate ESPN. In the run up to the US presidential elections, the site was visited by millions of people per day checking its predictions. Other articles on FiveThirtyEight cover statistical descriptions of changing patterns in drug usage, the pay gap between men and women, and Facebook usage. At newspapers like The Guardian and The Financial Times in the UK, Dagens Nyheter in Sweden, and The Washington Post and The New York Times in the USA, data journalism has become an important part of how the news is presented. For example, The Washington Post have looked at the demographic balance in China[1] and segregation in the US[2]. Ulmanu has built a system for collecting data on environmental defenders who have been killed helping the

[1] https://www.washingtonpost.com/graphics/2018/world/too-many-men/
[2] https://www.washingtonpost.com/graphics/2018/national/segregation-us-cities/

environment.[3] She also created 'Dark Side of Guardian Comments', an interactive app that allowed users to try out moderating the comments section of a newspaper (see Figure 1).[4]

Many bloggers and citizen journalists also produce high quality articles visualising and describing everything from inner city segregation[5] to the use of the #MeToo hashtag[6]. The public can burst into what Rheingold (2002) calls 'sudden epidemics of cooperation', including forms of 'peer-to-peer journalism'.

Despite the limitations, we stress that computational sociologists and mathematical modellers working within universities do in fact have tools that can help journalists to better deal with the challenges. Bloggers regularly use and refer to academic work and, for example, the FiveThirtyEight election model builds on Bayesian reasoning and regression models[7]. With respect to using statistics and visualisation, the main challenge for academics is to make sure that best practice is adopted throughout the media. Indeed, the Financial Times now educates and sets standards for best practice in data visualisation[8].

There is also a deeper challenge that is not yet addressed in data journalism, that of establishing causal explanations. This is an area in which the fields of analytic sociology and computational social science build around an approach called the micro-macro loop (Schelling, 1978; Coleman, 1986; Hedström, 2005; Raub et al., 2011, Macy & Willer, 2002, Sumpter et al. 2012). Macro structures, such as segregation patterns, the spread of ideas online or the rise of social movements, should and can be explained by human behaviour and interactions at the individual-level. There are now a good number of high-quality case studies where this approach is applied to, for example, online discussions (Garcia & Schweitzer, 2012; Garcia et al. 2017). In society, we have studied ethnic segregation in schools using the Schelling model as a basis for a statistical investigation of tipping points (Spaiser et. al., 2018) and used agent-based models to test hypotheses about the emergence of democracy (Spaiser & Sumpter, 2016). Computational social science has the ambitious aim to not work merely with statistical descriptions but to embed causal explanations, often through the use of mathematical models (Lazer et al. 2009). While blogs such as Nicky Case[9] and Complexity Explorables[10] have been used to explain how many micro-macro models work, what is still missing is a coupling between model and data[11].

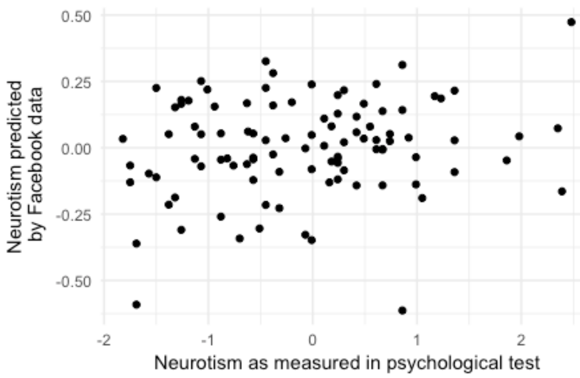

Figure 2 Investigating Cambridge Analytica. We revisited the original analyses of correlations between Facebook likes and personalities and, through a statistical investigation of the original data set in R, we identified important limitations. Specifically, we found that (1) personality could only be identified for the most active of Facebook users; (2) the reliability of likes was limited, so that if we pick two random people then at best, one can identify the more neurotic only 60% of the time; (3) a trait like neuroticism becomes meaningless when comparing the neuroticism of a would-be American gun owner with the neuroticism of a Nirvana fan.

[3] https://www.theguardian.com/environment/ng-interactive/2018/feb/27/the-defenders-recording-the-deaths-of-environmental-defenders-around-the-world
[4] https://monicaulma.nu/projects/6628997
[5] https://www.citylab.com/amp/article/553898/
[6] https://medium.com/@erin_gallagher/metoo-hashtag-network-visualization-960dd5a97cdf
[7] https://fivethirtyeight.com/features/how-the-fivethirtyeight-senate-forecast-model-works/
[8] https://www.ft.com/content/3b59f690-d129-11e7-b781-794ce08b24dc
[9] http://ncase.me
[10] http://rocs.hu-berlin.de/explorables/explorables/
[11] https://cacm.acm.org/magazines/2018/3/225484-computational-social-science-computer-science-social-data/fulltext

3 Significance and Scientific Novelty

The project starts from the premise that the gap between academic research and data journalism is too wide, especially considering the short time scale on which society is changing. In the context of computational social science and the micro-macro loop, we can see several weaknesses of data journalism: short deadlines, a need to react to events as they happen and to provide simplified explanations, mean that the understanding of a problem provided by newspaper articles and/or visualisations can be shallow. One of the biggest pieces missing from the puzzle is causation, the very aspect that the micro-macro loop and the modelling cycle aims to address. While data journalism is good at showing societal change, be it in segregation, in the rise of the right, algorithmic bias or in popularity of Youtubers, the problem of teasing out the underlying reasons for these changes remains, in many case, unaddressed.

The answer we propose is using a combination of data science, the micro-macro loop from sociology and mathematical models that communicate results in a way that explains issues to the reader. We will develop our methodology through a series of examples. In the long run, the goal is for social scientific concepts and practices to become widely used among data journalists and, via analysis of current events, for these to inform public debate. This project is especially timely given that computational social science, as predicted a decade ago (Lazer et al. 2009), is now in a position to transform how society is understood (Keuschnigg et al. 2018).

4 Preliminary and previous results

As a proof of concept, we have already started to develop our approach to a number of pressing societal issues. For example, in the wake of the Cambridge Analytica data scandal we looked at claims by the company's CEO what they could use Facebook data to identify users' personalities and then target them (Figure 2). Personality-based research has revealed correlations between what people 'like' on Facebook and their answers in personality tests (Kosinski et al. 2012). Our work is featured in articles written by Sumpter for The Daily Telegraph and The London Evening Standard, was presented in front of 200 people at the Royal Institution and is to be used as part of a forthcoming BBC Radio 4 documentary on targeted advertising. Further work by David Sumpter in writing a popular science book *Outnumbered* has looked at issues

As wide-ranging from the effect of fake news and echo chambers to the rise of the extreme right in Sweden (Figure 3) and gender discrimination in Science[12].

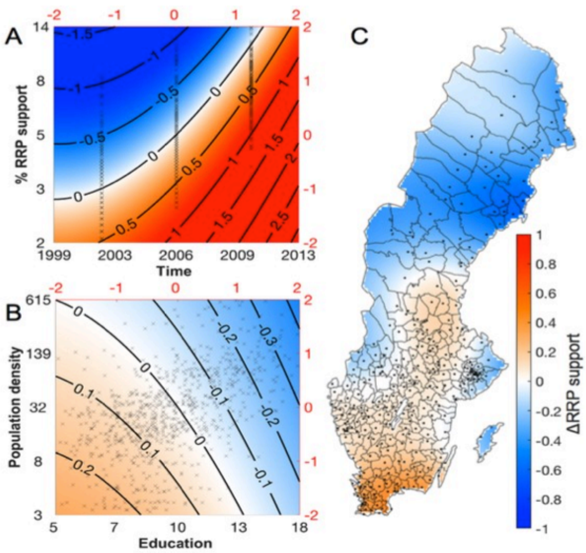

Figure 3 Rise of the Swedish democrats: In this project we looked at factors leading to the increase in support for far right parties. We created a website 'Last night in Sweden' which allowed the user to investigate relationships between crime, immigration and support for right-wing parties. This is a controversial area and we haven't yet gone public with this research, but we have used a Bayesian dynamical systems approach to study how Sweden is changing as a society (Blomqvist, Mann & Sumpter, in preparation). The results show the support for the extreme right is not a function of local immigration levels, but it does increase in areas with low population densities.

[12] Several examples of this work can be found at www.collective-behaviour.com

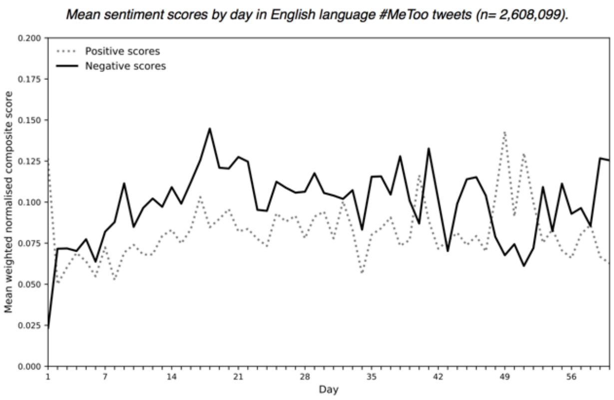

Figure 4 Mapping social movements: In this project we have looked at patterns of connectivity and discourse in relation to several emergent uprisings, campaigns, and debates. The approach allows us to assess sentiment on social media, for example, amidst the #MeToo campaign in 2017.

Simon Lindgren has been using computational social science methods to map the emergence and functioning of ad-hoc political campaigns and social movements online (Figure 4). He was able to provide analyses — posted on social media accounts — of the hashtag ecosystem surrounding #BlackLivesMatter, as well as sentiment analyses of 10 million tweets, showing different phases of the campaign. Similarly, the different types of attention that the public devoted to the simultaneous news of an actual terrorist attack in Sinai, and a false alarm about an attack in London, in November 2017 was quickly mapped and posted on Twitter.

Up to now, much of Sumpter's research has been conducted in spare time or as side-projects. Additionally, with a small grant to invite speakers and organise activities from Uppsala's Centre for Interdisciplinary Mathematics, we have engaged PhD students in becoming 'mathematical activists'[13]. Part of our aim is to formalise activities like these in a directed research programme.

Torill Kornfeldt regularly covers science, biotechnology and emerging technologies for some of Sweden's leading publications, including Dagens Nyheter, Sveriges Radio, Ny Teknik and Forskning & Framsteg. She has already started to develop the journalistic tools needed for an effective feedback loop between the project and the media, evaluating the usefulness of the developing tools from this project, as well as a strong public outreach[14]. During 2017 Kornfeldt wrote a series of journalistic essays on socially disruptive effects of new technologies that included perspectives from sociologists, philosophers and researchers within arts, humanities and gender studies. Articles covered topics such as biased algorithms, gender norms in social media, AI that would protect nature and political choices assisted by programs. Collaborators, Monica Ulmanu and John Burn-Murdoch webpages show further examples of the data journalism and visualisation on which this project will build. (Figure 1).

5 Project description

In each of the above projects, we have made small steps towards a better understanding micro-macro structure of these problems. In the proposed research we aim to do much more. Our approach to these problems is still relatively unstructured, in the sense that we build up an informal approach to each system but don't have a framework for analysis tools which allows them to be reused. The VR interdisciplinary grant we apply for now will allow us to formalise our research approach and to extend to further examples. Our project will develop a rigorous framework for addressing societal problems using data science and mathematical modelling.

5.1 Method and implementation

We will create a set of toolboxes for looking at each problem. These tools can be broadly classified as being either *statistical analysis* or *explanatory models*. Figure 5 illustrates the workflow for the approach, imagining in retrospect how we would deal with an analysis of a scandal in January 2018 when YouTuber Logan Paul's video of a suicide victim spread

[13] http://www.math.uu.se/math.uu.se/department-of-mathematics/cim/activities/math-for-social-activism
[14] http://www.kornfeldt.se

widely on the platform YouTube[15]. The spread of an offensive video raises a number of questions. Firstly, we ask what factors lead YouTube to promote such a video? Using variables describing Logan Paul's YouTube account (how many followers he has, number of videos shared, data available on Social Blade ranking, genre of videos etc.) and comparing to other similar accounts, we would identify which of these are important in lifting Paul's video rankings. This is essentially a *prediction/regression* question, and can be effectively solved using logistic regression on the independent variables listed above. Another statistical analysis is then *sentiment analysis* of the views expressed by users of YouTube, on the video by Paul and by videos created in response to the original video (Garcia & Schweitzer, 2012; Garcia et al. 2017).

These statistical analyses will then be combined with an explanatory approach. Two parts of our toolkit would be applied to the Logan Paul example. Firstly, we would use *social contagion model* to look at the spread of both videos and opinions about the Logan's post. It is often assumed that videos become viral, as in it is people who share them, but in the case of YouTube, a lot of views are driven by the YouTube algorithm. We would look at the balance between these routes for promotion. The second explanatory model activated in this example is cultural evolution. Over a timescale of months and year, the culture on YouTube about what is 'acceptable' changes and YouTube can find itself out of step with its users. Initially, one finds that 'shock' content like Logan Paul's is asked for by its users, but as other users are exposed to this content a backlash evolves. This second part of our approach goes beyond mere statistical description to an underlying mechanistic micro-macro understanding of the phenomena. It invokes the micro-macro loop.

Complementing our statistical and modelling approach, we will use an investigative journalistic approach to talk to the engineers behind this particular algorithm and also experts who have worked on similar algorithms. For example, in this case, Social Blade collect statistics over a long period and can provide their own understanding of the outcome of any particular video. On the other hand, since Social Blade are a private company who make money by helping people promote themselves on YouTube, the question is the degree to which they will release this information. It is here an investigative journalistic approach is needed. The journalistic contribution can also lift up a wider social perspective of how young men like Logan Paul become influential and whether this is good for society as a whole. This can in turn lead to wider questions about changing society, which could potentially be modelled by the explanatory model approach (i.e. cultural evolution).

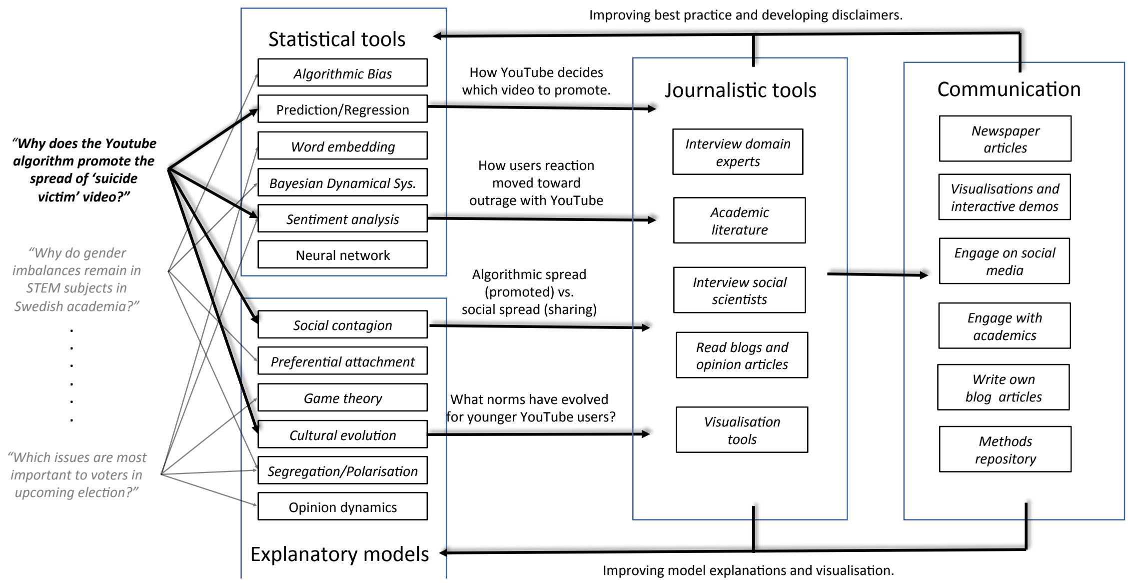

Figure 5 How our approach will be applied and how results will feedback in to imporvements.

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[15] http://www.bbc.com/news/newsbeat-42786609

The Logan Paul example is provided to give a concrete description of the steps we take. Figure 5 illustrates how each new problem will activate a new set of tools to address the problem. The three Postdocs within the project have distinct roles: Statistical Methods (SM), Explanatory Models (EM), and Computational Social Science (CSS). The SM postdoc will work closely together with EM and Sumpter in order to build and fit models to the data. The CSS postdoc and Lindgren will concentrate on grounding the project in a micro-macro approach, avoiding pitfalls of some mathematical modelling that it just looks at statistical patterns. The CSS will also serve as a connection to the journalists Kornfeldt, Ulmanu & Burn-Murdoch, grounding the story in causation. The journalists will not simply report on the research, but also apply their own toolset to investigate the problem, finding out potential causal mechanisms which modelling can then test. The mathematical newsroom will be an open forum for the spread of ideas.

Statistical tools: There already exist a wide range of statistical analysis tools to address these problems: *Prediction/regression* models, including multivariate linear/logistic regression and Principal Component Analysis, are widely used in modern data mining to predict personality, future behaviour or to classify people into targeted groups; *Algorithmic bias* testing can be used to see if an algorithm (e.g., for targeted advertising) is unfairly favouring certain groups (Kleinberg et al, 2016); *Bayesian dynamical systems* is an approach developed within the Uppsala group for establishing causal relationships in time series data (Ranganathan et al, 2014); *Sentiment analysis* allows emotional contagion to be studied on social networking sites such as Twitter and YouTube; *Word embedding* establishes vector representations for words from a corpus, allowing semantic relationships between words to be identified and detects stereotypes in everyday language use (Garg et al. 2018); and *Neural networks* have been recently used for predictive text and chatbots (Vinyals & Le, 2015). The main scientific development on our part is not necessarily the methods themselves but determining a way of utilising these techniques as rapidly and accurately as possible in the context of emerging societal questions.

The major theoretical question we address with respect to statistical methods is: when should we use a particular method in a data journalism context and how should we communicate about these methods? Each case study will show us how statistical tool choice influences the resulting journalism. Instead of just picking our 'favourite' model, we will think more deeply about both the choice of appropriate models given the problem we are addressing and how we present interpretation of those models. For example, the choice of using logistic regression or neural networks to solve a classification problem can influence how the results are interpreted. The first can be described as "a statistical model shows", while the latter can be described as "a machine has learnt that", while from a mathematical point of view there is very little difference between these two approaches.

As a key part of the project, in joint work between Postdoc SM and the journalists in the project, we will write a form of 'disclaimer' for each of these methods when used in a scientific context. One example can be found in the interpretation of word embeddings. When researchers published results showing these methods produced sexist outputs, it was unclear in much of the media reporting whether it was the 'algorithms' or the 'humans', on whose data the method was based, who were actually sexist (Caliskan et al., 2016). Our 'disclaimers' will carefully address these issues and encourage best practice.

Explanatory models: Statistics help us to find patterns in social data where they exist. Explanatory models allow us to make sense of these patterns. They allow us to answer questions such as: How do the algorithms used increasingly in industry, media and governance interact with human social behaviour? How would an event play out with different algorithms? Primarily, models help us provide micro to macro explanations of social phenomena that transcend mere statistical description. It is here the interplay between computational social science and applied mathematics can help journalists move toward a more causal approach to understanding and reporting events.

There already exist several micro-macro mechanistic models, originating from sociology, that will guide our approach: Social contagion use epidemiological models to explain behavioural contagions and tipping points (Granovetter 1978), as well as to explain spread of information, such as Twitter hashtags (Mønsted et al, 2017); *Preferential attachment* is a family of models have been able to explain social inequality and the adoption of certain technological platforms (Albert and Barabasi 2002); *Game theory* are canonical in studying problems of collective action (Ostrom 2000); *Cultural evolution* can explain how cultural blocks emerge from inter-individual interactions (Axelrod 1997). And can identify emerging patterns in large databases of cultural production and consumption, such as Spotify and Amazon.com; the *Segregation* model of Schelling (1971) shows how strong segregation can arise from weak preferences over many agents' movement decisions; *Opinion dynamics,* including bounded confidence models (Hegselmann and Krause 2000) can be used to explain the clustering or polarisation of political beliefs over time (Sobkowicz et al. 2012).

It is here that we will potentially make the biggest technical innovation in the project, and that we gain the most through journalists, mathematicians and social scientists working together. Although widely used by social scientists, there are few openly available tools to model interactions between individuals and show how model choice and parameters affect observable data. We will develop a set of tools in python that interface between data and models. Note again, that the pilot studies listed in Figures 1-4 make the required micro-macro loop. For example, to study the rise of extreme right-wing parties in Sweden we have used a Bayesian dynamical system approach to quantify the rise, but also considered an underlying social contagion model as the underlying explanatory model. This ability to interface between statistics and explanation is central to our approach. As another example, 'infection' models to monitor the spread of hashtags online is popular but often invokes the wrong micro mechanism (Lerman, 2016).

While journalism has moved ahead in data-visualisation and communicating statistics, the challenge in our project is to incorporate explanatory models in to articles. The best way to do this is through interactive visualisations, where the user investigates 'what-if' scenarios about how the world changes. A good example of this is 'The Parable of the Polygons' by Nicky Case, which illustrates the Schelling segregation model[16]. Currently, Burn-Murdoch is currently working on a visualisation to illustrate how bias manifests itself in algorithms. Building on work by Pro-publica on black boxes in sentencing[17], he is looking at the mathematical impossibility in achieving fair false positive rates across groups, while maintaining model calibration (Kleinberg et al. 2016). Ulmanu has used interactive apps in order to investigate the relationship between how we perceive, for example, gender imbalance in sports or how newspapers moderate comments (Figure 1). Working together with Sumpter, Lindgren, EM and CSS, they will create small, interactive apps that allow readers to investigate the micro-mechanisms that drive change in our society.

In this project we will only work with data from sources that are publicly available and that are compliant with the General Data Protection Regulation (GDPR). Further details on our data policy are available in the Ethical Considerations section.

5.2 Public Engagement

While, in our earlier work, managed to communicate effectively in the media about models, this work is (from the perspective of academia) on an ad-hoc basis. Our project will look at different media models more rigorously. For example, we will ask: Is it better to work together with traditional newspapers? Are video blogs more effective than written ones? How should we use platforms like Reddit and Twitter to effectively communicate? Are live meetings with people the most effective form of communication?

16 http://ncase.me/polygons/
17 https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing

We will work with both traditional media outlets like well-established newspapers, radio programs, magazines and similar, as well as creating and evaluating our own channels for outreach such as Youtube, twitter and other. As it can be difficult to establish a new audience on these types of platforms we will constantly evaluate how well we reach our target audience. By working with both traditional media and our own channels we ensure that we can test and evaluate our methods in several different settings and that they are well adapted to the journalistic toolbox.

We will actively try different methods of engagement. For example, we have previously conducted experiments in schools around micro-macro mechanisms. These experiments served both to collect in data for a scientific study and to educate school kids about how segregation occurs in society (Tsvetkova et al., 2016). A powerful extension to this would be to have the media cover experiments as they are carried out. Articles about researchers active engagement in the community can potentially capture the public's imagination more than reports on research that has already been carried out. Sumpter regularly presents his research for high school students, teachers, pensioners and other groups. Lindgren also gives public lectures regularly to a variety of interest groups, as well as makes appearances in the news media. In the age of social media, direct contact with people in the real world, where attention is fully focussed on the presenter, can be one of the most effective forms of outreach. We will maintain an online presence for the project that is separate from the individual projects we do with media partners.

5.3 Timeplan and organisation

We break our approach down in to five work packages. The first two are the statistical and modelling toolkit developments. The second two make the transition from maths to media, and the last one is a system of self-evaluation and development.

WP 1: Statistical tools. (contributors Sumpter & SM). We will build up a shared Python library for analysing and modelling data. We will develop a set of disclaimers (Kornfeldt & SM) explaining powers and limitations of different statistical models.

WP 2: Explanatory models (contributors Lindgren, Sumpter & EM). We will develop a toolbox of explanatory model libraries and develop ways of visualising and explaining models.

WP 3: The projects centre is the mathematical media room, where all participants will contribute. This will be run by Kornfeldt, who will keep track of the important stories. The media room will interact and respond effectively to requests from outside media. It will act together with WP 4, but maintain independence from the communicators, such as Ulmanu and Burn-Murdoch.

WP 4: News communication. We will be involved in (on average) one newspaper article per fortnight, working on four or five stories at any one time. For example, Ulmanu, Burn-Murdoch and other journalists will ask for assistance on projects. The journalists will maintain editorial independence and use WP3 as a resource. Working with traditional media also includes adapting our material to the formats and needs of different publications and editor, which also ensures that the toolbox can aid different types of journalism.

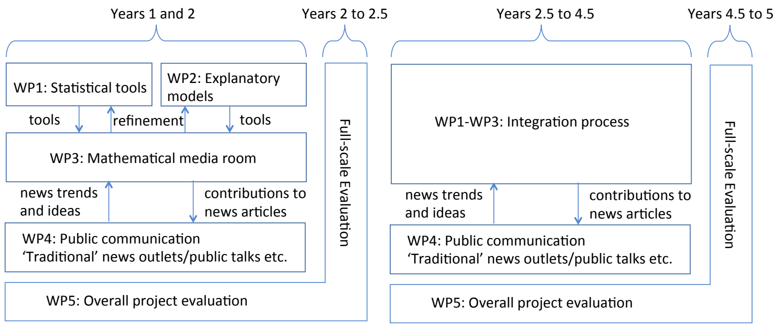

Figure 6 How the workpakages fit together

WP 5: We will also critically analyse the project itself from a social science perspective. This part will be led by social scientists, Lindgren and CSS, who will work together with other participants to better understand the degree to which we are bettering causal understanding through our approach. This will happen both at the end of the 2nd year and 5th years. We will do a full evaluation of the project so far and concentrate on writing articles and reports about the project itself. This will involve a reduction of daily activities in order to properly understand what works in communication and what doesn't and to study our own communication methods. Such thorough evaluation is not usually available to those working in media.

Figure 6 shows how the work packages will be organised in time.

6 References

Albert, R., & Barabási, A. L. (2002). Statistical mechanics of complex networks. *Reviews of Modern Physics*, 74(1), 47.

Allcott, H., and Gentzkow, M. (2017) Social media and fake news in the 2016 election. *Journal of Economic Perspectives* 31, no. 2 : 211-36.

Axelrod, R. (1997). The dissemination of culture: A model with local convergence and global polarization. *Journal of Conflict Resolution*, 41(2), 203-226.

Bakshy, E., Messing, S., and Adamic, L.A. (2015) Exposure to ideologically diverse news and opinion on Facebook. *Science* 348, no. 6239, 1130-1132.

Caliskan, Aylin, Joanna J. Bryson, and Arvind Narayanan. "Semantics derived automatically from language corpora contain human-like biases." *Science* 356, no. 6334 (2017): 183-186.

Coleman, J. S. (1986). Social theory, social research, and a theory of action. *American journal of Sociology*, 91(6), 1309-1335.

Del Vicario, M., Zollo, F., Caldarelli, G., Scala, A., and Quattrociocchi, W. (2016) The Anatomy of Brexit Debate on Facebook. *arXiv preprint arXiv:1610.06809*.

Garcia, D., Garas, A., & Schweitzer, F. (2017). An agent-based modeling framework for online collective emotions. In *Cyberemotions* (pp. 187-206). Springer, Cham.

Garcia, David, and Frank Schweitzer. (2012) Modeling online collective emotions. In *Proceedings of the 2012 workshop on Data-driven user behavioral modelling and mining from social media*, pp. 37-38. ACM.

Garg, N., Schiebinger, L., Jurafsky, D., & Zou, J. (2018). Word embeddings quantify 100 years of gender and ethnic stereotypes. *Proceedings of the National Academy of Sciences*, 115(16), E3635-E3644.

Granovetter, M. (1978). Threshold models of collective behavior. *American Journal of Sociology*, 83(6), 1420-1443.

Hedström, P. (2005). Dissecting the social: On the principles of analytical sociology. Cambridge: Cambridge University Press.

Hegselmann, R., & Krause, U. (2002). Opinion dynamics and bounded confidence models, analysis, and simulation. *Journal of Artificial Societies and Social Simulation*, 5(3).

Lazer, D., Pentland, A. S., Adamic, L., Aral, S., Barabasi, A. L., Brewer, D., ... & Jebara, T. (2009). Life in the network: the coming age of computational social science. Science 323(5915), 721.

Lerman, K. (2016)"Information is not a virus, and other consequences of human cognitive limits." *Future Internet* 8, no. 2: 21.

Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. *Econometrica*, 47(2), 263-292.

Keuschnigg, M., Lovsjö, N., & Hedström, P. (2018). Analytical sociology and computational social science. Journal of Computational Social Science, 1(1), 3-14.

Kleinberg, J., Mullainathan S., and Raghavan, M. (2016)."Inherent trade-offs in the fair determination of risk scores." *arXiv preprint arXiv:1609.05807*

Kosinski, M., Stillwell, D., & Graepel, T. (2013). Private traits and attributes are predictable from digital records of human behavior. *Proceedings of the National Academy of Sciences*, 110(15), 5802-5805.

Macy, M. W., & Willer, R. (2002). From factors to factors: computational sociology and agent-based modeling. *Annual Review of Sociology*, 28(1), 143-166.

Mønsted, B., Sapieżyński, P., Ferrara, E., & Lehmann, S. (2017). Evidence of complex contagion of information in social media: An experiment using Twitter bots. *PloS One*, 12(9), e0184148.

Ostrom, E. (2000). Collective action and the evolution of social norms. *Journal of Economic Perspectives*, 14(3), 137-158.

Pariser, E. (2011). *The filter bubble: what the Internet is hiding from you*. New York: Penguin Press.

Ranganathan, S., Spaiser, V., Mann, R. P., & Sumpter, D. J. (2014). Bayesian dynamical systems modelling in the social sciences. *PloS One*, 9(1), e86468.

Raub, W., Buskens, V., & Van Assen, M. A. (2011). Micro-macro links and microfoundations in sociology. *The Journal of Mathematical Sociology*, 35(1-3), 1-25.

Russell, J. A. (1980). A circumplex model of affect. *Journal of Personality and Social Psychology*, 39(6), 1161.

Schelling, T. C. (1971). Dynamic models of segregation. *Journal of Mathematical Sociology*, 1(2), 143-186.

Spaiser, V., Hedström, P., Ranganathan, S., Jansson, K., Nordvik, M. K., and Sumpter, D. J. T. (2018) Identifying complex dynamics in social systems: A new methodological approach applied to study school segregation. *Sociological Methods & Research* 47 (2), 103-135.

Spaiser, V., and Sumpter, D. J. T. (2016) Revising the human development sequence theory using an agent-based approach and data." *Journal of Artificial Societies and Social Simulation* 19, (3) (2016).

Sobkowicz, P., Kaschesky, M., & Bouchard, G. (2012). Opinion mining in social media: Modeling, simulating, and forecasting political opinions in the web. *Government Information Quarterly*, 29(4), 470-479.

Sumpter, David JT, Richard P. Mann, and Andrea Perna. "The modelling cycle for collective animal behaviour." *Interface focus* 2, no. 6 (2012): 764-773.

Tsvetkova, M., Nilsson, O., Öhman, C., Sumpter, L., and Sumpter, D. J. T. (2016) An experimental study of segregation mechanisms. *EPJ Data Science* 5(1), 4.

Vinyals, O., and Le, Q. (2015) "A neural conversational model." *arXiv preprint arXiv:1506.05869*.

Vosoughi, S., Roy, D., and Aral, S. (2018) The spread of true and false news online." *Science* 359, 1146-1151.