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Clemens Apprich

Always Be Filtering

Filters lie at the very heart of today's machine learning systems. And because machines process human – that is biased – data, these systems exacerbate existing inequalities in society and technology. In particular the homophilic principle of data analysis can be seen as a longstanding rule of segregation, buttressing most filter algorithms (e.g. recommendation systems). With algorithmically-enhanced systems of pattern recognition, the question of how to publicly share information about these algorithms and investigate them for bias has become crucial. Instead of the still persistent assumption that algorithms are somehow hidden in a 'black box', inaccessible to human reasoning, the following contribution seeks to develop new forms of critique vis-à-vis filtering algorithms. Hence, a critical reflection of filtering mechanisms, which ultimately decide for us what to include and what to exclude, needs new approaches. It is therefore important to develop a hands-on approach, by confronting the theorisation of filters with actual machine learning techniques (e.g. by studying online machine learning courses). This will help to unpack some of the mechanisms of algorithmic decision-making processes and build the basis for a genuine engagement with their real-world implications.

Schlagworte: algorithmic filters, machine learning, recommendation systems, critical data studies, pattern discrimination

Filters are everywhere. Visible or not, they structure our way of thinking, communicating, and decision-making. They determine the way we see the world and, consequently, how the world sees us. Initially defined as a "piece of felt through which liquid is strained,"¹ filters have always been essential to human life. They have been used throughout history to purify water, but also to improve the safety of less vital needs. In 1888 the brothers Max, Ludwig, and Julius Bunzl, after moving their father's company for sewing articles from Bratislava to Vienna, began to manufacture paper in a small mill in lower Austria. There the first cigarette filter was produced from crepe paper in 1927 to keep tobacco flakes out of the smoker's mouth. After the seizure of power by the Nazi regime, the Bunzl family had to emigrate to England and expanded their business with an independently-run company named American Filtrona that was set up in the United States in 1954.² Soon the company became the exclusive supplier to the two biggest cigarette producers at that time, Imperial Tobacco and Gallaher Group. And with increasing concerns over the harmful effects of cigarette consumption, the sales of newly developed filters to reduce tar levels peaked in the 1970s.³ During the 1980s, when smoking rates were falling in Western countries, the tobacco industry began to heavily invest in Asian markets, introducing dual carbon filters as a way to mitigate the health risk.⁴ However, filters did not make inhaling tobacco less harmful by any means. With more than eight million people dying of smoking each year, they can

1 o.A., Filter, *Etymonline*, 24.05.2017, <https://www.etymonline.com/word/filter> (31.3.2023).

2 For a detailed company history, see: Our History, *Bunzl plc*, <https://www.bunzl.com/~media/Files/B/Bunzl-PLC/content-pdfs/bunzl-history-sep-2015.pdf> (14.9.2020).

3 Filters, back then, not only were considered to reduce tar in cigarette smoke, but also made it possible to minimize the amount of tobacco whilst maintaining the same cigarette length. Both lower tar levels and lower costs for tobacco boosted the sales of cigarette filters.

4 In particular, China's 'open-door policy', initiated by Deng Xiaoping in 1978 to open up China to foreign businesses, allowed for the importation of cigarettes for the first time. In 1987, Shanghai Cigarette Factory launched the first cigarette using carbon dual filters in China. Soon after Japan and Korea followed this trend.

in fact be called “the deadliest fraud in the history of human civilization.”⁵ And still, they come wrapped in paper printed to look like cork – a reminiscence of a carefree era when the biggest concern with smoking was smeared lipstick.

The fraudulent use of filters has many scenes: from power plants to the auto industry to algorithmic trading.⁶ This breach of law is not without irony, given the fact that ‘transgression’ is at the very core of any filtering system. Filters do not only push the boundaries of what is legal or illegal, but also go beyond our understanding of what is helpful or harmful – or considered to be alive or dead. By setting the standards for modern water filtration systems, the Pasteur-Chamberland filter, a simple device invented in 1884 by Charles Édouard Chamberland, one of Louis Pasteur’s assistants in Paris, arguably saved the lives of millions of people.⁷ Yet its actual impact transgressed the practical application of filtering out bacteria and other disease-producing microbes: with this ‘epistemic thing’⁸ it was possible to discover an infectious material in the filtrate that was able to pass through the tiny pores of the porcelain filter and, unlike a toxin, could replicate itself. The discovery of viruses as a hidden form of life, which were first observed on tobacco leaves, fundamentally changed our view of the world. A century later, it even inspired a young computer scientist at the University of Southern California’s School of Engineering to write a program that could ‘infect’ other programs “by modifying them to include a possibly evolved copy of itself.”⁹ Since then, viruses have haunted not only the *actual*, but also the *virtual* world – a world which is not itself physically existing, but brought to life by myriads of filters in the form of electro-mechanical switches, logic gates, or network protocols. With this short historical outline in mind, the following contribution will sketch out a conceptual framework to better understand filtering under digital conditions. I will do so by firstly posing the problem of algorithmic filtering in digital cultures, secondly formulating a research agenda in the context of critical data studies, and thirdly applying the framework to the example of collaborative filtering, a technique which has become central to most of today’s recommendation systems.

Algorithmic Filtering

Today the process of filtering information from data has become an issue of great socio-political and economic concern. Given the massive dissemination of digital media technologies over the last decades, data has not only increased in size, but also in its level of organisation, complexity, and control.¹⁰ Every time we send an email, click through a website, upload an image, fill in an online form, write a post, buy a ticket, or use a recommendation engine, we produce chunks of data. However, ‘Big Data’ does not explain much without taking into account the epistemologies, technologies, as well as

5 Quote by Robert N. Proctor, professor of History of Science at Stanford University (see Pagan Kennedy: Who Made That Cigarette Filter?, in: *New York Times Magazine*, 06.07.2012, <https://www.nytimes.com/2012/07/08/magazine/who-made-that-cigarette-filter.html>) (31.3.2023).

6 For example: High-Frequency Trader Indicted For Manipulating Commodities Futures Markets In First Federal Prosecution For ‘Spoofing’, *United States Department of Justice*, 10.02.2014, <https://www.justice.gov/usao-ndil/pr/high-frequency-trader-indicted-manipulating-commodities-futures-markets-first-federal> (31.3.2023).

7 See Bert Hansen: The Filter of Life, *Science History Institute*, 09.10.2016, <https://www.sciencehistory.org/distillations/the-filter-of-life> (31.3.2023).

8 Hans-Jörg Rheinberger: *Toward a History of Epistemic Things. Synthesizing Proteins in the Test Tube*, Stanford 1997.

9 Fred Cohen: Computer Viruses - Theory and Experiments, Bethlehem/PA 1984 (paper originated from a security seminar at Lehigh University), <https://web.eecs.umich.edu/~aparaksh/eecs588/handouts/cohen-viruses.html> (31.3.2023).

10 See Viktor Mayer-Schönberger and Kenneth Cukier: *Big Data: The Essential Guide to Work, Life and Learning in the Age of Insight*, London 2013.

histories and politics behind algorithmic filters that sift through, process and interpret these vast amounts of data for us. By imposing identity on input data, in order to filter – that is to discriminate – signals from noise, pattern recognition algorithms pose one of the most urgent and important challenges in digital cultures today.¹¹ Far from being a neutral process, the computational delineation and application of patterns is in itself deeply problematic. Even more so as political, social and economic decision-making are increasingly based on modern advances in artificial intelligence, machine learning, and computational models. Not only do these models depend on massive amounts of data, a fact which creates its very own problems, but they also work towards the segmentation of people, thereby destabilising the idea of an egalitarian and democratic society.¹² Of course, automated tools to assess criminality or credit risks have been around for decades. But with large scale data sets and more complex computational models, our understanding of the world has fundamentally changed: the organisation of culture, as well as social ordering are deeply enmeshed with algorithmic filter technologies, and it is therefore becoming harder to ignore their economic, socio-political and ethical implications.

By applying filters, we constantly (re-)create them, particularly since the act of filtering information from data lies at the very heart of how we see and perceive the world.¹³ By the same token, one can argue that filtering has always played a central role in human, as well as non-human cognition. We need to filter in order to make sense of the world. And the conditions to do so have become digital ones, as Friedrich Kittler argued with reference to Shannon's theory of information; his 'discourse networks' (*Aufschreibesysteme*) are historically contingent filtering systems to produce order in an otherwise chaotic data stream.¹⁴ Filtering under digital conditions has obviously changed the way data gets produced, filtered and analysed over the last years, especially since machine-based learning techniques are being deployed on a massive scale to automate these processes.¹⁵ Predicting the future based on our past, these filter machines reinstate old forms of social segregation, such as class, race and gender, through defaults and paradigmatic assumptions about the homophilic 'nature' of connectivity.¹⁶ While first attempts have been made to discuss questions of 'algorithmic identity politics' within digital cultures in North America,¹⁷ such a critical approach is yet to be seen in Europe. Even though everyone is talking about digitality, most initiatives in digitisation are still based on the promise of what is possible, instead of a reflection of what is desirable. Digital filtering, in this regard, is not only shaped by and shapes commercial as well as governmental interests, but also strongly influences

11 See Clemens Apprich, Wendy Hui Kyong Chun, Florian Cramer and Hito Steyerl: *Pattern Discrimination*, Minneapolis/Lüneburg 2019.

12 See, for example, Virginia Eubanks: *Automating Inequality. How High-tech Tools Profile, Police, and Punish the Poor*, New York 2018; Safiya Umoja Noble: *Algorithms of Oppression. How Search Engines Reinforce Racism*, New York 2018; Cathy O'Neil: *Weapons of Math Destruction. How Big Data Increases Inequality and Threatens Democracy*, London 2016.

13 See Wendy Hui Kyong Chun: Filtering System, in: Timon Beyes, Robin Holt and Claus Pias (ed.): *The Oxford Handbook of Media, Technology, and Organization Studies*, Oxford 2020, 238-245.

14 Friedrich A. Kittler: *Discourse Networks 1800/1900*, Stanford 1990. 369-372.

15 See, for example, Dominique Cardon, Jean-Philippe Cointet, Antoine Mazières: Neurons Spike Back. The Invention of Inductive Machines and the Artificial Intelligence Controversy, in: *Réseaux*, Nr. 211, May 2018, 173–220; Adrian Mackenzie: *Machine Learners. Archeology of a Data Practice*, Cambridge/MA 2017; Ethem Alpaydin: *Machine Learning. The New AI*, Cambridge/MA 2016.

16 Wendy Hui Kyong Chun: *Discriminating Data. Correlations, Neighborhoods, and the New Politics of Recognition*, Cambridge/MA 2021, in particular Chapter 2.

17 See, for example, John Cheney-Lippold: A New Algorithmic Identity. Soft Biopolitics and the Modulation of Control, in: *Theory, Culture & Society*, Nr. 28:6, 2011, <https://doi.org/10.1177/0263276411424420>.

how we do research; a fact that should be recognised if we do not want to completely surrender to the new schoolmasters in machine learning and AI research.¹⁸

Working through real-world problems requires real-world data, and – contrary to the popular but also scientific belief – this data is far from being a valid representation of the world.¹⁹ Since data is never ‘pure’²⁰ and algorithms are never fully ‘objective,’²¹ a critique of the implicit assumptions and patterns coded into machine-learning processes is crucial. What complicates the study, though, is the fact that these algorithms are in a state of permanent negotiation between human and non-human agents.²² Dealing with their ephemeral nature is a challenge shared with the already established software studies.²³ Due to the awareness that software “is extremely difficult to comprehend”²⁴ and that despite “being inherent to software, algorithms are quite difficult to analyse,”²⁵ it offers a number of hints for the study of algorithmic filtering. Being constituted by “wider data assemblages”²⁶ that encompass technological as well as cultural, economic, social, and political apparatuses,²⁷ data-driven algorithms represent a mode of thinking, a form of knowledge, a set of practices, and a way of looking at the world.²⁸ This, of course, includes a technical perspective as well. Hence, studying (and teaching) automated filter mechanisms, in spite of – or precisely because of – their complex nature, necessitates an engagement with machine learning techniques, as we can test and experience them with open-source technologies (e.g. by using Google’s TensorFlow or exploiting Large Language Models). Here we need to adopt a different course than most of the current research done in cultural and media studies, which dodges the technical aspect of algorithmic filtering and merely deals with its cultural, social, and political effects. In line with software studies, the aim is to develop a hands-on approach, by confronting the theorisation of filters with actual machine learning techniques (e.g. by studying online machine

18 See Clemens Apprich: TensorFlow – A Playground for Neural Networks, in: Simon Denny, Timon Beyes, Robin Holt, Claus Pias, Bettina Steinbrügge (ed.): *Proof of Stake: Technological Claims*, Milan 2022, 111–114.

19 While the underlying data of machine-learning processes is often seen as a kind of ‘pure’ representation of the world, most of the data we are in fact dealing with in algorithmic filtering and machine learning is ‘dirty’ data, that is data which is inaccurate, incomplete or inconsistent. See Hito Steyerl: A Sea of Data. Apophenia and Pattern (Mis-)Recognition, in: *e-flux*, Nr. 72, April 2016, <https://www.e-flux.com/journal/72/60480/a-sea-of-data-apophenia-and-pattern-mis-recognition> (31.3.2023).

20 Lisa Gitelman, Virginia Jackson: Introduction, in: Lisa Gitelman (ed.): *Raw Data Is an Oxymoron*, Cambridge/MA 2013, 114, here 3.

21 danah boyd, Your Data is Being Manipulated, in: *Data & Society: Points*, October 4, 2017, <https://points.datasociety.net/your-data-is-being-manipulated-a7e31a83577b> (31.3.2023).

22 As can be seen by the example of Google’s PageRank, see Bernhard Rieder: What is in PageRank? A Historical and Conceptual Investigation of a Recursive Status Index, in: *Computational Culture*, Nr. 2 2012, http://computationalculture.net/what_is_in_pagerank (31.3.2023).

23 See, for example, Adrien Mackenzie: *Cutting Code. Software and Sociality*, New York 2006; Matthew Fuller (ed.), *Software Studies. A Lexicon*, Cambridge/MA. 2008; Wendy Hui Kyong Chun: *Programmed Visions: Software and Memory*, Cambridge/MA 2011.

24 Chun: *Programmed Visions*, 2.

25 Mackenzie: *Cutting Code*, 44.

26 Andrew Iliadis, Federica Russo: Critical data studies: An introduction, in: *Big Data & Society*, Nr. 3:2, 2016, <https://doi.org/10.1177/2053951716674238>.

27 Rob Kitchin: Big Data, new epistemologies and paradigm shifts, in: *Big Data & Society*, Nr. 1:1, 2014, <https://doi.org/10.1177/2053951714528481>.

28 Rob Kitchin, Tracey Lauriault: Towards critical data studies: Charting and unpacking data assemblages and their work, in: *The Programmable City Working Paper*, Nr. 2, 2014, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2474112 (15.2.2020).

learning courses). This will help to unpack some of the mechanisms of algorithmic decision-making processes and build the basis for a genuine engagement with their real-world implications.²⁹

Critical Data Studies

Algorithmic filtering needs to be reflected technically, ethically, politically, economically and epistemologically if we want to better understand automated and self-learning machines that organise digital cultures, and, as a consequence, the way we live together. As media scholar Bernhard Rieder points out, current studies often either have a quite narrow view on code – disregarding wider epistemological contexts – or predominantly focus on societal effects.³⁰ However, doing critical work with algorithmic filtering involves an understanding of both, the technical structure of algorithms, as well as the social and cultural context in which those algorithms are operating. A mere instrumental examination of filter algorithms will necessarily miss the underlying epistemological and political effects of data filtering, in particular with emergent phenomena such as algorithmic identity³¹ and algorithmic life.³² By the same token, only focusing on the social impacts often falls short of a deeper understanding of the technological requirements, fundamental for the production and interpretation of data. In this regard, critical data studies offer an innovative and vibrant new research field that aims for an awareness among researchers of the forms of knowledge being produced with algorithmic filtering and their own role in that process.³³ By applying critical theory to data, big or not, this field of research deals with power dynamics enacted in the code and develops new modes of critique vis-a-vis the technical, organisational and political issues emerging with new data regimes.³⁴ It ultimately calls for a wider critical reflection of data analytics and new epistemological positions associated with it, even more so, as machine learning techniques have boosted the performativity in automated filtering over the last few years.³⁵

While media studies are still often focused on historical research to understand digital technologies, thereby always at risk of uncoupling its agenda from current debates and pragmatic interventions, research approaches in data science often tend to present-based and positivistic approaches when discussing and actually building digital media technologies. Only at the interface of these two lies the potential to critically reflect on digitisation and to foster the democratic use of data. Here it will be important to forge new alliances between the fields and to set up a research agenda able to create alternative data paradigms in digital cultures. In order to do so, we'll have to challenge two persistent misconceptions in relation to digital filtering: on the one hand, the very idea that algorithmic filter mechanisms, because of their indifference to human decision-making, provide more 'objective'

29 Inga Luchs, Clemens Apprich, Marcel Broersma: Learning Machine Learning: On the Political Economy of Big Tech's AI Online Courses, in: *Big Data & Society*, Nr. 10:1, 2023, <https://doi.org/10.1177/20539517231153>. For a similar approach, see Bernhard Rieder: *Engines of Order. A Mechanology of Algorithmic Techniques*, Amsterdam 2020; and Mackenzie, *Machine Learners*.

30 Rieder: *Engines of Order*, 98-100.

31 See Cheney-Lippold: *A New Algorithmic Identity*.

32 Louise Amoore, Volha Piotukh (ed.): *Algorithmic Life. Calculative devices in the age of big data*, New York 2015.

33 danah boyd, Kate Crawford: Critical Questions for Big Data, in: *Information, Communication & Society*, Nr. 15:5, 2012, 662–679.

34 Craig Dalton, Jim Thatcher: What does a Critical Data Studies look like and why do we care?, in: *Society + Space*, 12.05.2014, <https://www.societyandspace.org/articles/what-does-a-critical-data-studies-look-like-and-why-do-we-care> (31.3.2023).

35 Rob Kitchin: Big Data, new epistemologies and paradigm shifts, in: *Big Data & Society*, Nr. 1:1, 2014, <https://doi.org/10.1177/2053951714528481>.

results; on the other hand, the corresponding belief that the underlying mechanisms, in particular in machine learning, are somehow hidden in a ‘black box’, inaccessible to human reasoning. Both assumptions treat machines as an alien entity. Now the trick would be to acknowledge this alien position of the machine and, at the same time, accept the mutual interrelationships we entertain with it. Because we are subject to the same symbolic (i.e. language-based) order, filter algorithms eventually (re-)produce cultural bias, in the form of racist, sexist, and classist beliefs;³⁶ a fact responsible for much of the growing toxicity in our online worlds and, at the same time, allowing for new research activities.

Most of today’s machines process human – that is biased – data. Hence, machine bias is not solely a technical problem; rather, automated tools re-introduce inequity precisely because they are being inserted into an already discriminatory social world. By the same token, social bias is now hardcoded into the algorithms and can thus become an object of analysis. Machine code has the potential to make visible what was previously hidden, be it in political institutions, bureaucratic apparatuses, or informal networks.³⁷ To tap into this situation, I propose a model that seeks to capture the complex interplay of – at least – three conceptual levels when it comes to algorithmic filtering:³⁸ First, the syntactic level of data. In the context of machine learning this refers to the dataset from which the features for the learning process are extracted. Here the question of how the dataset is being arranged is crucial to the validity of the data, in particular in its self-contradicting denomination as ‘raw data’. Data do not exist as things-in-themselves, or, as Lisa Gitelman and Virginia Jackson write: “Data need to be imagined *as* data to exist and function as such, and the imagination of data entails an interpretative base.”³⁹ As such, data always already refer to a second, semantic level: that of information. The interpretation of data is based on specific frameworks, whereas “[e]very discipline and disciplinary institution has its own norms and standards for the imagination of data.”⁴⁰ These norms and standards help us to filter the necessary information in a given situation by connecting data to real-world applications. Here information “refers to a mode of knowledge that is no longer reflective or contemplative but performative and pragmatic.”⁴¹ While, in recent years, a lot of research efforts have been devoted to the understanding of the interrelation between data and information – by frequently confusing the two concepts – knowledge as the third level of analysis has all too often been overlooked. Now with regard to data-driven algorithms, the pragmatic level of knowledge might provide a way to better understand how information is eventually filtered from data, not least because “data produce and are produced by the operations of knowledge production.”⁴² To make this point clear I will apply the conceptual model of data – information – knowledge to collaborative filtering as one of the dominant techniques within algorithmic filtering today.⁴³

36 See Apprich et al.: *Pattern Discrimination*.

37 Using machine learning-tools to diagnose bias and inequality in past and existing institutions is also part of the “Data Fluencies”-initiative, run by the Digital Democracies Institute at Simon Fraser University.

38 See also Clemens Apprich: Data Paranoia: How to Make Sense of Pattern Discrimination, in: Apprich et al.: *Pattern Discrimination*, 99–123.

39 Gitelman and Jackson: *Introduction*, 6.

40 Ibid.

41 Tiziana Terranova with reference to Jean-François Lyotard; Tiziana Terranova: The Concept of Information, in: *Theory, Culture & Society*, Nr. 23:286, 2006, <https://doi.org/10.1177/0263276406023002115>.

42 Gitelman and Jackson: *Introduction*, 6.

43 Collaborative filtering is a central component of recommendation engines, which, according to Ethem Alpaydin, are at the forefront of machine learning today (see Alpaydin: *Machine Learning*, 118–123).

Collaborative Filtering

Collaborative filtering is all around us. As a central part of recommender systems, collaborative filtering tells us what to buy (Amazon, Alibaba), which videos to watch (Youtube, TikTok), which songs to listen to (Spotify), whom to be friends with (Facebook, WeChat), and whom to date (Tinder). Collaborative filtering allows for *simultaneous* recommendations, which means that the system recommends an item to a user not solely based on the user's individual preferences, but on the interests of all the other users. Hence, the idea is to find users similar to the target user and to weight their interest in an issue or item.⁴⁴ By collecting information from peer users, the recommendation system then generates recommendations for a target user.⁴⁵ It simply assumes that people like things similar to other things they like, and things that are liked by other people who are like them. What matters is not so much the individual node, but the ties to other nodes. So contrary to the usual conception of 'individualisation' and 'personalisation' in our online world, we are, in fact, constantly being lumped together to analyse and predict our future behaviour. Correlations are not solely based on our individual actions and histories, but rather the histories and actions of others 'like' us.⁴⁶ As Alexander Galloway writes with regard to the protocological power of filtering systems: "What makes [collaborative filtering] so different from other survey-based predictive techniques is the use of powerful algorithms to determine and at the same time inflect the identity of the user."⁴⁷ But how then is this identity being determined? How is similarity being assessed?

A recommendation system calculates relationships between users and items to capture patterns of similarity in the assumption that those are somehow meaningful.⁴⁸ To do so, collaborative filtering draws a utility matrix on a syntactic level, with an endless row of everything a user has clicked on, watched, purchased, and so on, and a table representing all the other users within a given network. The system then correlates the data to make its predictions for a single user, a process that can be done automatically by so called embeddings.⁴⁹ The big advantage of embeddings is that the system does not have to explicitly ask the user to rate an item, to search for something, or to rank a collection of items from most to least favourite (e.g. star ratings, scores, online games), but can easily measure it by collapsing a large number of variables (e.g. online behaviour, viewing time, location) into a few underlying factors.⁵⁰ And while the goal is to encode as many semantic relations, that is as much information, as possible, the system also needs to be small enough to discriminate the data effectively. To solve this issue, also referred to as sparsity and scalability problem, embeddings are used to capture

44 See Shuyu Luo: Introduction to Recommender System, *Towards Data Science*, 10.12.2018, <https://towardsdatascience.com/intro-to-recommender-system-collaborative-filtering-64a238194a26> (31.3.2023).

45 For example, Amazon's by now famous "People who buy x also buy y".

46 This is what Wendy Chun and others have called the "homophilic principle" of network analysis, which provides the 'logic' to recommendation systems; see Laura Kurgan, Dare Brawley, Brian House, Jia Zhang, Wendy Hui Kyong Chun: Homophily: The Urban History of an Algorithm, in: *e-flux Architecture*, October 2019, <https://www.e-flux.com/architecture/are-friends-electric/289193/homophily-the-urban-history-of-an-algorithm> (31.3.2023).

47 Alexander Galloway: *Protocol. How Control Exists After Decentralization*, Cambridge/MA 2004, 114.

48 To learn about and also program a recommendation system, you can visit Google's Machine Learning Crash Course: <https://developers.google.com/machine-learning/recommendation> (31.3.2023).

49 In a Deep Neural Network, embeddings are usually represented as hidden layers. See, for example, Will Koehrsen: Neural Network Embeddings Explained, *Towards Data Science*, 10.02.2018, <https://towardsdatascience.com/neural-network-embeddings-explained-4d028e6f0526> (31.3.2023).

50 This is often done with matrix factorization, a method to extract a set of latent features for an individual user (e.g. to measure how much a movie fits into this set of latent features).

and fold the important information of a high-dimensional space in a low dimensional space.⁵¹ Now there are many mathematical techniques to do this; however, two methods have proven to be very powerful when creating an embedding for machine learning systems: Principal Component Analysis and Factor Analysis. As data reduction techniques, they are both very similar, which is also the reason why they often get confused.⁵² Yet, the benefit of Factor Analysis is that it can deal with data that was implicitly collected by collapsing a large number of variables into a few underlying factors. For example, a retailer may not be able to directly ask about a customer's class, gender, or race (although the marketing department is very much interested in this information); instead, it can measure the likelihood of these categories by combining a set of variables (i.e. proxy-data).

This last point refers to the knowledge-aspect of collaborative filtering: By capturing the latent structure of a user or query set, the recommendation system is reliant on implicit knowledge about how it should filter the information from the existing data. Here the 'neighbourhood' is not only referring to classification or clustering algorithms (e.g. k-nearest-neighbour), but also to the idea that 'proximity', 'similarity' and 'closeness' are valid categories to structure the data. "Neighborhood technologies"⁵³ are built on the assumption that similarity breeds connection, an idea that has led to the formation of 'homophilic' tendencies online as well as offline.⁵⁴ Based on their likes and dislikes users are clustered into segregated communities, with the effect that historically grown power relations are now hidden in the 'natural preferences' of individual users to surround themselves with their peers. The issue with this kind of identity politics is that seemingly immutable categories such as race, class, and gender are being imbedded in 'less crude' categories such as Zip codes, buying behaviour, or social credit scores. Yet, collaborative filtering is by no means a 'neutral' phenomenon; the collection and analysis – that is the production – of data is based on a performative and therefore pragmatic framework of interpretation that is always presupposed. This explains why the patterns that are uncovered through collaborative filtering are precisely those patterns that for centuries have produced discriminatory practices, such as racism, sexism, or classism. Since the notion of the neighbourhood with its underlying principle of homophily has found its way into algorithmic code and network technologies, it comes with no surprise when filtering machines begin to discriminate along these same lines.⁵⁵

Conclusion

What all algorithmic filtering and machine learning models are ultimately trying to achieve is to find patterns that can then be applied to unseen data. Now these models do not operate in some kind of digital Lalaland, but are actually processing real-world, that is our data. In particular, the idea that similarity breeds connection can be seen as a longstanding rule of segregation, which still buttresses

51 See Google's Machine Learning Crash Course on 'Embeddings', <https://developers.google.com/machine-learning/crash-course/embeddings/video-lecture> (31.3.2023).

52 While PCA is a linear combination of variables to create one or more principal components, FA is a measurement model of latent factors that cannot be directly measured but instead are observed through the relationships they cause in the variables. See Karen Grace-Martin: The Fundamental Difference Between Principal Component Analysis and Factor Analysis, *The Analysis Factor*, <https://www.theanalysisfactor.com/the-fundamental-difference-between-principal-component-analysis-and-factor-analysis> (31.3.2023).

53 See Tobias Harks and Sebastian Vehlken (ed.): *Neighborhood Technologies. Media and Mathematics of Dynamic Networks*, Zürich/Berlin 2015.

54 See Miller McPherson, Lynn Smith-Lovin, James M Cook: BIRDS OF A FEATHER: Homophily in Social Networks, in: *Annual Review of Sociology*, Nr. 27, 2001, 415–44.

55 See Chun: *Discriminating Data*.

most of today's filter algorithms and recommendation systems.⁵⁶ These systems work by segmenting people by interests, political views, or sexual orientation, thereby deepening bias and further inscribing inequality into society and technologies. In order to study and explore these discriminatory practices in algorithmic filtering, we do not have to invent yet another discipline, but rather take the interdisciplinary potential of a genuine collaboration between data science, critical theory, and media studies seriously. Critical data studies, in this regard, can be seen as a research field across these disciplines that fosters "critical thinking about algorithms and considers how best to research them in practice."⁵⁷ As such, it can help to better understand discrimination with regard to data-driven politics, and to critically reflect on identity politics in digital cultures. With algorithmically-enhanced systems of pattern recognition, the question of how to publicly share information about these algorithms and investigate them for bias has become crucial. Hence, a critical reflection of filtering mechanisms, which ultimately decide for us what to include and what to exclude, needs new approaches, which help to make pattern recognition and filter algorithms more transparent and accountable.

The tremendous growth of data produced on the Internet has made it much more difficult to effectively extract information from it. The problem is not so much that recommendation systems help us to collaboratively filter information from an ever-increasing data stream, but that the underlying patterns correspond in so many ways to a retrograde identity politics. The network logic behind collaborative filtering (i.e. behind most of today's Internet platforms) is truly haunted by its own past, thereby causing the much-discussed (classist, racist, sexist) disparities in today's network culture. What we thus need is knowledge about how specific patterns are being employed to filter information from data; even more so since online platforms built on collaborative filtering (e.g. Amazon, Lieferando, Uber) are now reorganising everyday life and thus change our understanding of what a neighbourhood actually is and how it works.⁵⁸ Here media studies, and in particular critical data studies, might provide a valuable resource to develop tools of analysis as well as research skills to detect data bias and algorithmic inequity. They could provide a space where well-researched concepts from the humanities and arts, such as identity, interpretation, representation, or meaning, are taken up and applied to the current debates around digitisation, machine learning and algorithmic filtering.

What is more is that the triangulation between data, information and knowledge ultimately points to another level, which holds those three together: truth. The way we, as a society, filter information from data to make knowledge-based decisions, is contingent on negotiation processes that are neither fully comprehensible, nor knowable. This entails the uncomfortable truth that it won't be enough to simply accumulate knowledge if we want to face the challenges that come with algorithmic filtering systems (i.e. including the automation of labour processes as well as generative machine learning models). Rather, we have to move from the know-how to the know-why, which implies a common understanding about the goals and direction of building and implementing digital media technologies. It also implies the acknowledgment of the fact that we, by applying algorithmic but also any other filter, have to discriminate in one way or another. The question, therefore, is not how to prevent bias and discrimination, but *why* we filter in this and not another way. Herein lies the 'ground truth' of algorithmic filtering, which has to be renegotiated again and again. In this regard, the study of filters can indeed

56 See Kurgan et al.: Homophily.

57 Rob Kitchin: Thinking Critically About and Researching Algorithms, in: *The Programmable City Working Paper*, Nr. 5, 2014, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2515786 (15.2.2020).

58 See also current neighborhood platforms such as *nachbarschaft.net*, *nebenan.de* or *nextdoor.de* that are also shaping today's digitally mediated urban space.

open a new horizon for media and cultural studies – all the more when we consider their central role for our democratic future.