Google, what are algorithms?

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October 14, 2020
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Abstract

This study examines public discourses surrounding algorithms and artificial intelligence with the aim of adding to the growing body of research on the algorithmic imaginary (Bucher, 2017). While the bulk of research in this domain has focused on people's theories about social media content curation algorithms, people draw on many other contexts to explain what algorithms and artificial intelligence are and how they work. We assemble and explore a dataset of text-based Google Search results for queries like 'what are algorithms?' or 'how does AI work?'. Using LDA topic modelling, we identify the main themes that recur across the explanations, showing that alongside social media, explanations of AI tend to be situated in domains like business and management, gameplay and strategy or simulating biological systems. We propose that the contexts in and through which people encounter algorithms can be framed as: (1) work; (2) leisure and personal interest; (3) societal questions and governance; and (4) non-digitally-native associations. This provides a broader perspective for future research into the algorithmic imaginary to examine.

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1. Introduction

One of the comments on a blog post entitled 'What Is The Instagram Algorithm and How to Beat It?' (Sociablesquare, Nov 2019) reads: "Useful post. I finally understood the Instagram algorithm".

Over the past few years countless articles have been published online aiming to explain algorithms and artificial intelligence to their often non-expert and non-technical readers. Written in the form of click-bait articles, wikipedia-like entries, discussion forum responses, online newspaper fillers or 101 introductory tutorials, text-based accounts explaining algorithms and AI abound online. In a time when Googling has become one of the fastest ways of knowing (Lynch, 2016), search results yielded by queries like 'what are algorithms?' or 'how does AI work?' form some of the common ground that people share in formulating answers to these questions. With the aim of adding to the growing body of research on the algorithmic imaginary (Bucher, 2017), we therefore examine the ways in which artificial intelligence algorithms[1] are explained in texts found through Google's search engine. In what ways and through which of their applications do people explain algorithms? And how, in turn, do people make sense of these invisible and intangible entities, processes or systems? Or: through what means do readers like the one mentioned above reach a level of understanding at which they feel comfortable to say that they have "finally understood" an algorithm?

The body of research dealing with the ways in which people understand algorithms focuses heavily on speculations of the users of content curation algorithms and recommender systems of mainstream social media platforms (Rader & Gray, 2015; Eslami et al., 2016; Bucher, 2017; DeVito, Gergle & Birnholtz, 2017; Meyers West, 2018; Bishop, 2019; Cotter, 2019; Alvarado et al., 2020). We choose to focus on existing text-based explanations of algorithms and artificial intelligence more broadly, in order to propose alternative domains to focus on and to identify some of the contexts in which people encounter these systems. Through what other applications or aspects of algorithms, besides social media, could future research

[1] As we are interested in artificial intelligence algorithms, the terms 'algorithms' and 'artificial intelligence' are used co-constitutively throughout our work. Even though the terms are often used interchangeably in public discourse, research dealing with the algorithmic imaginary tends to avoid explicit mention of artificial intelligence. Addressing both in unisom can be a productive integration for discussions on the algorithmic imaginary.

access the algorithmic imaginary? Based on a quantitative analysis of Google search results explaining algorithms and artificial intelligence, we propose four main contexts in and through which people encounter algorithms, beyond merely social media. Namely, (1) work; (2) leisure and personal interest; (3) societal questions and governance; and (4) non-digitally-native associations.

Answering the question ‘What is the Instagram Algorithm?’, the blog post mentioned above begins by stating that “The Instagram algorithm is the heart and brain behind the Instagram app.” (Sociablesquare, Nov 2019).

The brain is one aspect that figures frequently in both technical and non-technical explanations of artificial intelligence algorithms; technically speaking, it is a continuous source of inspiration for the development of artificial neural networks, while its replication is simultaneously a popular sci-fi fantasy central to narratives on possible futures of AI. We view the brain as one example of a non-digitally-native association that people adopt to explain and speculate about algorithms. Much like social media, the brain is a concept that people can relate to, while - very unlike social media - it is not algorithmically constituted. In other words, it serves as a metaphor, which builds peoples’ understanding of concepts or phenomena by relating them to other concepts that individuals (think) they understand. Seeing as such metaphorical leaps can lead to false conclusions, it is relevant to stress that we are not researching the *validity* of people’s understanding of AI. Rather, we are interested in what people *think* that AI is; how they *imagine* it works. Our exploration of the brain then serves both, as an example of a methodological approach to studying the algorithmic imaginary, and as a contribution to the discussion on the ways in which people make sense of algorithms; through embodied concepts like the brain.

The next section outlines scholarly approaches to understanding how people make sense of algorithms, followed by a section that highlights the concerns and shortcomings of the currently dominant social media-focused approaches in the field. Building on this, we discuss our own methodology and findings.

2. Making sense of algorithmic encounters

Encounters make way for understanding. As Bucher (2017) puts it, the encounter envelopes the situation and the emotional experience that together shape people’s perceptions of algorithms. In this section we synthesize some of the main approaches that scholars have taken in studying algorithms critically, with a focus on factors that shape algorithmic encounters. We discuss some of the frames scholars use to approach algorithmic understanding, ranging from concrete theories to complex assemblages, and highlight some of the challenges and confounding factors muddling people’s access to algorithmic knowledge.

2.1. The algorithmic imaginary and its folk theories

Reflecting on the meeting points of people and algorithms, Bucher (2017) asks: ‘[h]ow do they experience and make sense of these algorithms, given their often hidden and invisible nature?’. In the study driven by this question, Bucher (2017) develops the notion of the ‘algorithmic imaginary’; a concept that has been since adopted and elaborated by many scholars in the field (for example: DeVito, Gergle & Birnholtz, 2017; Alvarado & Waern, 2018; Toff & Nielsen, 2018; Bishop, 2019; Cotter, 2019). The algorithmic imaginary is to be understood ‘as the way in which people imagine, perceive and experience algorithms and what these imaginations make possible’, rather than a way to term false belief (Bucher, 2017: 2). Thinking through this concept opens up a means of engaging with the affective dimension of encounters with algorithms and understanding them in terms of more than just machine-readable instructions. In our research, we are interested in further exploring this algorithmic imaginary.

Research about the ways in which people make sense of algorithms, particularly in light of their complex, invisible and intangible nature, often builds on the concept of folk theories (for example: Eslami et. al, 2015; Rader & Gray, 2015; DeVito, Gergle & Birnholtz, 2017; Meyers West, 2018; Toff & Nielsen, 2018); a concept adapted from fields like the cognitive sciences and anthropology (see for example: Keil, 2010;

Gelman & Legare, 2011). Gelman and Legare 'propose that mental content can be productively approached by examining the intuitive causal explanatory "theories" that people construct to explain, interpret, and intervene on the world around them, including theories of mind, of biology, or of physics' (2011: 379). Summarised as 'intuitive theories' or 'folk theories', reasoning along these lines forms the framework for analysing concrete working theories that make up the algorithmic imaginary of people with predominantly non-technical and non-expert knowledge of algorithms.

Such studies provide insight into the concrete mechanisms that people imagine taking place behind the scenes, primarily based on their own experiences. Rader and Gray (2015) found that 80% of their survey respondents (of 223) believed that an algorithmic entity prioritizes posts to show in their Facebook News Feeds based on what the system knows about them. Looking into the reasoning behind such speculations, Eslami et al. (2016) found that Facebook users believe that personal engagement with another user positively affects the amount of exposure to their content; that individual users' overall number of likes and comments makes their content more visible; or that some formats of social media contributions are more likely to appear than others. Bucher's (2017) findings echo some of these, for example that Facebook users view the algorithm as propelling the 'popularity game', but also offer alternate insights, such as that the algorithm is capable of 'ruining friendships'.

In other words, folk theories and beliefs offer a framework for understanding how people imagine that algorithms work in their daily lives, rather than how algorithms work on the terms of the computer scientists and software engineers who develop them.

2.2. The imaginary as an assemblage

Nevertheless, scholars like Rader and Gray (2015) raise an important point in saying that people's understanding of algorithms is generative in the context of the algorithmic systems themselves; the users are implicated in the feedback loops that are shaped by their actions. This echoes Gillespie's (2014) conception of algorithms as entanglements made up of recursive loops of the "calculations" of both algorithms and people.

Indeed, scholars often situate the theory/belief-oriented level of analysis outlined above within the broader notion that algorithms constitute socio-technical assemblages. This is a means to string the discrete theories together in a single assemblage of sorts, but, at the same, to highlight that algorithms' complexity cannot be captured on these terms alone. To Kitchin for example, it is 'most productive to conceive of algorithms as being contingent, ontogenetic, performative in nature and embedded in wider socio-technical assemblages' (2017: 16). Elements of this definition are echoed in much of the critical scholarly discourse on algorithms. The concept of a 'socio-technical assemblage' parallels for example Jasanoff and Kim's (2015) work on sociotechnical imaginaries or Seaver (2013) and Geiger's (2014) research on algorithmic systems. This systemic and assemblage-like conception of algorithms informs the way in which many scholars frame and approach algorithms in their research (for example: Kitchin & Dodge, 2011; Rader & Gray, 2015; Lee, 2018; Myers West, 2019; Alvarado et al., 2020). The algorithmic imaginary and so-called folk theories about algorithms can be understood as being enmeshed in and co-constitutive of these socio-technical assemblages; they are not mere side-products, but rather their integral components.

While this entangled, embedded nature of algorithms enriches the range of perspectives algorithms can be studied from, it is also viewed as a critical challenge to their access (Kitchin, 2017). Rather than as individual algorithms, algorithms usually operate in systems within wider networks of relations; in effect, this means that they are distributed entities, making an "algorithm" as such difficult to put a finger on. One of the ways in which they can be made tangible is through the spaces in which they take effect; meaning for example where they do work, make decisions, or direct other human and non-human agents. Kithcin and Dodge (2011) formulate a spatial conception of algorithms as code/spaces that can (and should) be studied with a spatial, situated approach. With spaces and software becoming mutually constitutive in places like modern-day airports or classrooms, the spatial dimension and impact of algorithms can be one way to tease apart these otherwise ubiquitous assemblages.

2.3. Relating to/with algorithms

Making sense of algorithms then, departs from situated encounters with them. It is relevant to note that a portion of these encounters might go unnoticed. Eslami et al. (2015) found that over half of the Facebook users they interviewed (25 of 40) were unaware of Facebook's News Feed curation algorithm prior to their interviews. 'Algorithm awareness', a term that Eslami et al. (2015) highlight in their research, is therefore a relevant precedent to reasoning about the algorithmic imaginary.

Encounters in which people are aware of their algorithmic interlocutors are shaped by a broad range of cognitive and psychological factors. Although studies on the algorithmic imaginary rarely discuss research into the cognitive and psychological factors that figure in people's interactions with software and machines, findings from fields like Human Computer Interaction could be informative for better understanding how people relate to and with algorithms. Lee (2018) for example finds that algorithms are judged as being efficient and lacking bias in contrast to humans in decision-making positions. Nevertheless, assessing humans through algorithms is perceived as demeaning and dehumanising. Findings like these suggest that contradictions and confounding factors may exist in peoples' responses to algorithms; if an algorithm is viewed as less biased than a human in the same position, why view its assessment as dehumanising?

To give a few more examples, mind attribution and anthropomorphism also come to play a role in this respect; viewed as mindful or human-like agents, algorithms are likely to evoke different kinds of experiences in their interlocutors than as inanimate instruction sets. Research into anthropomorphism in relation to machines suggests that humans tend to apply social rules mindlessly (Nass & Moon, 2000). That is, people are inclined to respond to computers socially, without necessarily athropocisising their interlocutor - neither intentionally, nor subconsciously. As for mind attribution, Gray and Wegner (2012) find that it is easier for humans to attribute brain-like qualities to an abstract piece of software, an algorithm, than to a humanoid robot. The evocation of mind in humanoid robots is challenging and makes us less eager to endow it with brain-like qualities. Cognitive phenomena behind the examples listed here, like pro-social behaviour or the uncanny valley, shape what Alvarado and Waern (2018) call the algorithmic experience, thereby tainting people's imaginaries.

2.4. Myths, gaps and barriers to understanding

Limitations to access and popular presumptions influence both, how people (can) engage with algorithms and what people understand them to be.

Often out of reach of the public for reasons of state or corporate secrecy, access to the algorithms that people interface with on a daily basis is largely restricted (Seaver, 2013; Kitchin, 2017). Next to individual factors like lacking technical knowledge or expertise of those outside the data science and AI communities, this poses a significant institutionalised barrier to understanding how these algorithms work. In response, the impetus to reverse-engineer algorithms as a means to make sense of them is echoed throughout the literature. Researchers conducting surveys or interviews detail people's own efforts at reverse-engineering the algorithms they encounter on a daily basis, for example in managing visibility on the Facebook News Feed (Rader & Gray, 2015) or YouTube's beauty vlogs (Bishop, 2019).

Given the often lacking algorithm awareness and easily manipulated algorithmic experience, scholars actively challenge the framing of algorithms as objective and rational agents (Gillespie, 2014; Kitchin, 2017). Gillespie (2014) has termed algorithmic objectivity a 'carefully crafted fiction', a 'fragile accomplishment', or a 'performed backstage'. This 'promise of algorithmic objectivity' (Gillespie, 2014) has widely been dispelled as a myth, to the extent that we would argue that the myth-ness of algorithmic objectivity - with the widely used notion of 'algorithmic bias' taking its place - has become one of the core elements in the algorithmic imaginary. Lacking algorithmic objectivity is an issue highlighted in both scholarly circles and popular media, particularly in relation to decision-making processes and governance (Rouvroy & Stiegler, 2016; Katzenbach & Ulbricht, 2019).

Some scholars highlight the religious, supernatural or mythical position that contemporary digital technologies assume (Mosco, 2005; Natale & Pasulka, 2019), which dispels the question of objectivity altogether. Popular concepts like ‘cloud computing’ or ‘networks’ are in this sense primarily viewed as systems of belief, or state of desire, as the implicit interconnectivity does not match up with reality (Natale & Pasulka, 2019). Studying the perceptions and portrayals of AI, Cave et al. (2018) find that people’s perceptions are often disconnected from the reality of technology; the narratives tend to be focused on utopian and dystopian extremes that instill unrealistic expectations, overconfidence, or, on the contrary, false fears. These studies point to a gap between technological realities and people’s understanding; a recurrent theme in findings about the algorithmic imaginary.

In summary, so far we have stressed that the algorithmic imaginary is best studied through its encounters; spaces in which intuitive theories on algorithms can be formulated. While concepts like ‘folk theories’ can be used to frame some of the mechanisms that people imagine behind the scenes, it remains important to acknowledge that algorithms are embedded in wider socio-technical assemblages, which are difficult to pin down through narrow mechanistic reasoning. A multitude of cognitive and social factors mould people’s encounters with algorithms; tendencies to anthropomorphize, popular notions like lacking objectivity and factors like lacking access taint both how people engage with algorithms and what they imagine them to be.

3. A social media-focused approach

To date, research dealing with the algorithmic imaginary has primarily focused on the limited context of content curation algorithms and recommender systems on mainstream social media platforms like Facebook, Youtube or Twitter. These platforms are widely pervasive in people’s daily lives and generally have low-threshold accessibility. Given the barriers and complexities in accessing the majority of algorithmic systems, their popular usage makes them a well-suited entry point to the algorithmic imaginary; social media platforms are the sites of countless aware algorithmic encounters. Building on the examples of research on folk theories and user beliefs about social media algorithms that we mentioned above, here, we elaborate further on this social media-focused approach to the algorithmic imaginary - its primary concerns, generalisable takeaways and shortcomings.

Working the dominant role in what others get to see across social media platforms or search engines, content curation algorithms become formative of the ways in which people learn to know themselves. In this sense they have become one of today’s “technologies of the self”, a concept explored by Foucault (1993) in the context of practices like diary writing, recently revisited in light of algorithms (Gillespie, 2014; Fischer 2020). Terms like the ‘quantified self’ (Lupton, 2016) denote a way of accessing one’s subjectivity, as well as that of others. Theories about the functioning of algorithms tend to be a personally engaging issue for many of their users, which means there are ample stories and experiences for scholars to study.

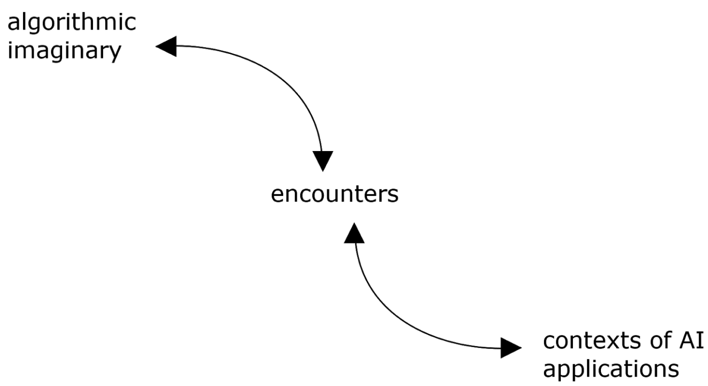
Algorithmic visibility management is one of the topics studied through social media platform users’ folk theories. Online visibility, or in many cases invisibility, is one of the more tangible traces of algorithmic work. As mentioned above, researchers find that social media users tend to use abductive reasoning, folk theories (Eslami et al., 2016), abstract theories (DeVito, Gergle & Birnholtz, 2017) or different forms of reverse engineering like gossip (Bishop, 2019) to speculate about content curation algorithms tasked with visibility management. Concrete and tangible traces of algorithmic work are therefore useful - if not necessary - to focus people’s speculations about algorithms.

The majority of recent studies on people’s understanding of algorithms is focused on non-technical and non-expert platform users. Bishop (2019) raises a concern over this binary approach; on one end algorithms tend to be studied in sites of technical expertise - at tech companies for example - and on the other through platform users' daily experiences, often stressing their lacking technical knowledge and expertise. This leaves large groups of platform users unaccounted for, for example those who lack knowledge of the technical dimension of given algorithms, but can nonetheless be considered their expert users by the nature of their work. Making a start at filling the gap, Bishop's own study focuses on Youtube's beauty vloggers 'whose feminised output positions them outside of the *technical*, yet whose work is contingent on algorithmic visibility' (2019: 2950). It is important to stress then, that the algorithmic imaginary need not be seen as restricted to theories built on own experiences, but extends to contexts in which their users adopt more systematic and professional approaches to making sense of them.

Concerns surrounding content curation algorithms and recommender systems are widely explored outside the academic context. Countless articles and blog posts detail 'how to beat the Instagram algorithm', influencers include 'insider tips' on visibility management in their weekly mailing lists and courses like the 'Beat The Algorithm' Academy have sprung up online. Popular media outlets like Mashable or VICE dedicate articles to the secrets behind Instagram's algorithm (Rosenberg, Jun 2018) or user's 'wild theories' about how TikTok's algorithm works (Haskins, Aug 2019). These are often the products of people's systematic efforts to grasp these systems and use them in line with their interest. Or, forms of what Seaver (2013) or Kitchin (2017) would call reverse engineering. Such material is indicative of the relevance of making sense of algorithms, and at the same time, can be studied in itself as an accumulation of current efforts in this direction.

In our research we (1) include these second-plus-hand explanations and mediations in our notion of algorithmic encounters and (2) propose to explore the algorithmic imaginary beyond the narrow focus on social media. That being said, existing social media-focused studies of the algorithmic imaginary provide a number of useful takeaways that can be productive in researching people's theories and beliefs in other contexts. The few mentioned here include: studying algorithms in contexts that people find personally engaging; focusing on concrete and tangible traces of algorithmic work; and including views of those that might escape a purely non-technical and non-expert group.

As the previous sections imply, the theoretical background of our research centres around the relationship between the algorithmic imaginary, algorithmic encounters and the contexts in which these encounters take place. Figure 1 serves to summarise and emphasize the connection between these concepts, which we continue to build on throughout this paper.



— Figure 1: a diagram visualising the relation between the algorithmic imaginary, algorithmic encounters and the contexts in which these encounters take place; the three core concepts referred to throughout this paper. —

4. Methodology

The abundant online resources explaining what algorithms are and how they work are our primary entry point into the algorithmic imaginary. Popular approaches in this domain involve interviews (Eslami et al., 2016; Bucher, 2017; Bishop, 2019; Alvarado et al., 2020), workshops (Cave et al., 2018) or surveys (Rader

& Gray, 2015; Zhang & Dafoe, 2019). Such studies generally question their participants about their experiences with and theories about algorithms to infer their imaginaries, rather than surveying pre-existing content on the topic.

To address the issue of identifying a wider range of contexts that people draw on to explain what algorithms and artificial intelligence are and how they work, we focused on public discourses on the topic of algorithms and AI. We chose to analyse the discourses and associations that permeate the ways in which people write about algorithms, without the pretext of being prompted for a causal theory. Such an exploration of a corpus of ‘found’ content lent itself to a quantitative approach, through which we could survey the breadth of public discourses before tunnelling into its individual strands.

Quantitative approaches in this domain have primarily been adopted in areas with easy access to large amounts of textual data, like tweets with particular hashtags (DeVito, Gergle & Birnholtz, 2017), articles from the New York Times’ archives (Fast & Horovitz, 2017) or films tagged ‘artificial intelligence’ on IMDb (Recchia, 2020). As Recchia (2020) argues, although literary research has likely already identified some of the most important key themes, computational approaches can point to notable patterns, nuances or undercurrents that can otherwise be overlooked. In the context of the algorithmic imaginary which has been heavily associated with content curation algorithms and recommender systems on social media platforms, we found this approach useful in suggesting new ways in.

4.1. Data collection and preprocessing

The quantitative part of our research consisted of a semantic analysis of text-based sources accessed through Google Search. We consider Google Search results as a viable proxy for public discourses; the search results obtained for queries like ‘what are algorithms?’ or ‘how does AI work?’ shape the understanding of those asking these questions. ‘Googling it’, or Google-knowing is today’s fastest way of knowing (Lynch, 2016). Scrolling and skimming through the answers that Google yields is a second-hand algorithmic encounter for many, thereby shaping their algorithmic imaginaries; as we summarised in Figure 1, such encounters interface between the algorithmic imaginary and its contexts. In a period that Fischer and Mehozay (2019) term the algorithmic episteme, blog posts, news articles or encyclopedia entries that make it through the search engine are products of the socio-technological features characteristic of digital media; namely, user-generated data, inter-connected platforms and algorithms. Table 1 summarises all the search terms used to make our dataset.

Google Search queries
what are algorithms
how do algorithms work
how to beat the algorithm
what is the algorithm
what is artificial intelligence
how does artificial intelligence work
how to beat artificial intelligence
what is AI
how does AI work
how to beat AI

— Table 1: the queries used in Google’s search engine to assemble a dataset for analysis. Text-based results from the first 25 pages for each of these queries were used. —

We used Python's *BeautifulSoup* library to gather the body of text from the individual search results pages for each of these ten queries. Texts from the first 25 Google Search results pages were collected; based on a manual check, these pages buried relatively deep down in the search results contained texts that were comparable to the first few results pages in their content and style. Although the queries are similar, each yielded more than 75% unique results.

The individual texts were preprocessed for analysis using the *nltk* and *gensim* libraries. As a means of preprocessing, each text was first tokenised. All words shorter than 3 characters and all English language stop words were removed. Bigrams were formed from the remaining tokens based on the scoring function introduced by Mikolov et al. (2013) and all the resultant tokens were lemmatized using *nltk*'s WordNet lemmatizer. Additionally, duplicates, texts consisting of fewer than 50 words and non-English language texts were removed.

4.2. Topic modelling and Word2vec

To explore this corpus of texts, we used a number of computational methods and reviewed a random selection of the texts themselves. To identify the main topics that are discussed across these texts we used a Latent Dirichlet Allocation (LDA) topic model (Blei, Ng & Jordan, 2003). LDA is a generative probabilistic model used for topic modelling in NLP, where each topic is represented by a probability distribution of specific terms - these terms can recur across topics. Each text in the dataset is treated as a bag of words and represented as a mixture of a chosen, finite number of topics. We supplement our analysis of the resultant topics by reading several texts from each of them, in order to get a better understanding of the kinds of discussions pertaining to each one.

To explore some of the associations between the terms in our dataset, we created a vector embedding model of the words with Word2vec (Mikolov et al, 2013). Word2vec is a method used in NLP to create vector representations that capture semantic word relationships; terms that share common contexts are located in close proximity in the model's vector space. Word2vec uses a shallow two-layer neural network to achieve this; we used the Skip-Gram implementation of the model described by Mikolov et al. (2013).

Both models were created using their respective *gensim* library implementations in Python. We further created graphs from our models using *networkx,* and used the *pyLDAvis* implementation of LDAvis (Sievert & Shirley, 2014), Gephi (Bastian, Heymann & Jacomy, 2009) and Tensorflow's Tensorboard Embedding Projector[2] as visualisation tools.

5. A topical overview of the algorithmic imaginary

Modelling the dataset of texts (n = 1847) using LDA, we arrived at ten topics made up of terms most characteristic for each of them. Prior to settling on ten topics, we had conducted a series of tests to determine the optimal number of topics and the LDA model parameters in line with our data. We selected the combination of parameters that yielded the highest coherence value (C_v = 0.453); we used the *gensim* implementation of the C_v coherence measure described by Röder, Both and Hinneburg (2015). The results presented here, in Table 2 and Figure 2, are from our final topic model with α = 0.1 and β = 0.01. These parameters represent the a priori estimate of the probability of each topic (α) and the probability of each term (β) respectively. The topic labels are based on our own interpretation of the corresponding clusters of most salient terms and informed by samples of texts from the dataset.

As Recchia (2020) notes, topics identified through similar quantitative methods are not necessarily novel to the field of AI narratives, but provide a useful overview and highlight some patterns as well as nuances that can otherwise go unnoticed. Indeed many of these topics have already been addressed in the literature.

[2] The Tensorboard Embedding Projector can be found here: https://projector.tensorflow.org/

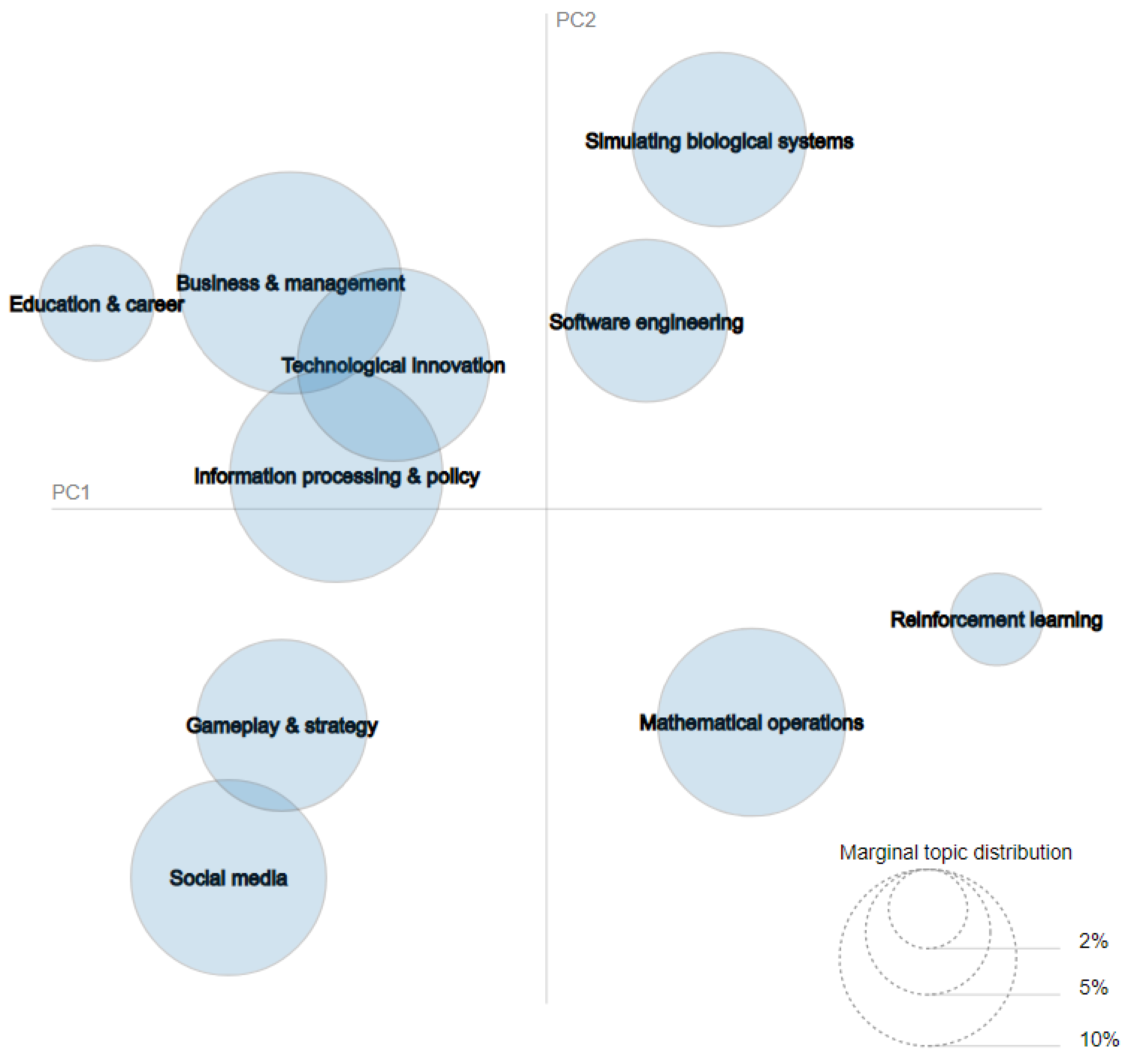
Cave et al. (2018) for example describe the future-oriented talk in discussing public perceptions of AI, while Lee (2018) studies perceptions of decision-making algorithms in a business and management setting. Nevertheless, we find that the majority of these topics are underrepresented in the domain of the algorithmic imaginary, which is primarily social media-focused.

LDA topics	20 most salient terms per topic	Percentage of texts in topic	Topic label
1	data; business; technology; company; service; customer; help; use; solution; industry; new; management; application; product; market; support; process; (work); information; development; provide	15.8%	Business and management
2	(algorithm); data; people; information; bias; say; decision; system; technology; use; human; need; risk; patient; individual; social; right; society; issue; public; research	14.5%	Information processing and policy
3	post; (algorithm); content; instagram; facebook; user; like; social media; people; time; video; marketing; engagement; (work); google; use; business; comment; way; share; want; page	12.2%	Social media
4	human; machine; technology; (work); (artificial intelligence); people; like; way; job; team; task; robot; think; future; need; world; intelligence; example; understand; new; well; time	11.9%	Technological innovation for the future
5	(algorithm); problem; number; example; time; program; step; use; sort; list; give; write; set; follow; code; value; input; array; function; solution; process	11.3%	Mathematical operations
6	intelligence; artificial; machine; human; learn; program; system; research; intelligent; neural network; science; computer; application; problem; technology; robot; field; information; brain; deep	9.7%	Simulating biological systems
7	game; play; player; like; human; say; time; new; world; beat; best; go; know; year; way; poker; google; look; alphago; strategy	9.4%	Gameplay and strategy
8	data; machine learning; learn; model; (algorithm); deep learning; image; training; science; (artificial intelligence); software; cloud; application; base; understand; use; program; like; train; type; python; (work); help	8.4%	Software engineering
9	program; student; science; job; online; (work); school; course; learn; research; university; technology; test; education; help; island; new; information; career; candidate; hire	4.2%	Education and career
10	learn; monte carlo; method; reinforcement learning; model; base; value; agent; (algorithm); action; example; network; state; sample; gridworld; policy; paper; problem; approach; deepmind; feature	2.7%	Reinforcement learning

— Table 2: A table showing the 20 most salient terms for each of the 10 topics and corresponding topic labels based on our interpretation. The terms are listed in descending order of importance for each respective topic. Terms constituent of the search queries were included in the model and are listed here in brackets, but are not included in the count to 20. —

Based on our LDA model, we find that the topics 'Business and management' (constituting 15.8% of the texts in the dataset) and 'Information processing and policy' (14.5%) are more prevalent in the dataset than 'Social media' (12.2%). Taking this as an indication of their dominance in public discourses on algorithms and AI, we can suspend the hesitation of these topics being potentially too 'technical' or 'expert' and enquire, for example, about the ways in which people make sense of decision-making or predictive algorithms in the context of the workplace (considering terms like 'company', 'management' or 'customer'), governance ('decision', 'society', 'public') or healthcare ('risk', 'patient').

A closer look at the texts in the dataset points to some of the ways in which algorithms might be viewed under these topics. A text labeled 'Business and management' defines algorithms as instructions *'introduced to automate trading to generate profits at a frequency impossible to a human trader.'* (Corporate Finance Institute, n.d.). The text proceeds to stress the process of 'algorithmic trading' whose rules are set *'based on pricing, quantity, timing, and other mathematical models'*. Although a more thorough study would need to be carried out in order to identify concrete user beliefs in the context of algorithmic trading, these brief extracts suggest that the theories and speculations that algorithmic encounters in this domain inspire are quite different from those in the social media-focused algorithmic imaginary. This is echoed by the relatively large intertopic distance between 'Business and management' and 'Social media', visualised in Figure 2, implying that their lexical contexts are different.



— Figure 2: A global view of our LDA topic model adapted from the web-based interactive visualisation made using the LDAvis system (Sievert & Shirley, 2014). Each topic is plotted as a circle in a two-dimensional plane. The centers of the circles are positioned according to the distance between the topics and projected into two dimensions using multidimensional scaling. The size of the circles is scaled according to the given topic's overall prevalence. —

Indeed, we find that the ways in which people explain algorithms in the lexical contexts denoted by the individual topic clusters are different and context-specific. Although ‘Gameplay and strategy’ overlaps with ‘Social media’, the primary rhetoric they share is a focus on ‘beating’ or ‘gaming’ algorithmic agents or systems; these two topics are both prevalent in the results for search queries like ‘how to beat the algorithm’ or ‘how to beat AI’. One ‘Gameplay and strategy’ text for example, discusses Google DeepMind’s AlphaStar AI which defeated professional StartCraft II players (Ghonshal, Jan 2019). The jargon and analogies used in this article have little in common with the concerns over online visibility management (Bishop, 2019) or working theories about Facebook’s underlying NewsFeed ‘popularity game’ (Bucher, 2017) discussed in the context of ‘Social media’. Instead, Ghonshal’s (Jan 2019) article recounts human-AI matches in turn-based games like Chess, Go or Shogi, explains that AlphaStar was trained on ‘*roughly 200 years’ worth of gameplay*’, or compares AI’s playing style to an ‘*alien*’, rather than a human- or machine-like strategy. We propose that researching the algorithmic imaginary across different lexical contexts can reveal interesting and relevant - although potentially opposing - insights into how people make sense of algorithms.

Further, in line with Recchia’s (2020) justification for the use of computational methods in studying AI narratives, we find that our topic model points to contexts of algorithmic encounters that might otherwise be overlooked. For instance, discussions of the algorithmic imaginary often depart from explaining algorithms in terms of *more than just* sets of instructions, code or functions (Bucher, 2017; Kitchin, 2017). Texts labeled ‘Mathematical operations’ however, constituted 11.3% of our dataset. Seeing as these mathematical operations, albeit put into layman’s terms, are often one of the first explanatory rhetorics that people searching for an answer to the question ‘what are algorithms?’ will get, considering a deeper layer of people’s theories about how the maths come together to form algorithms or AI could be questioned. In other words, what fills the gap in people’s perceptions between the functions and code that algorithms are explained through, and the emergent algorithmic systems that can, for example, operate customer service lines? Mathematical explanations of algorithms as such do not speak much to its imaginary, but people’s working theories about the mathematical operations behind them do occupy a noteworthy portion in associated discourses and should not, therefore, be overlooked.

5.1. A ‘way of doing’ as well as an agent

Next to identifying individual topics through our LDA model, we explored the model and our dataset horizontally, in order to formulate some comments on explanations of algorithms at large. We find that definition-level explanations of algorithms alone differ greatly across the texts in our dataset, suggesting that future research should be open in its a priori framing of ‘algorithms’ and perceptive of these nuances. Table 3 presents a selection of what we consider definition-level explanations of algorithms.

Namely, rather than as an agential entity, text-based explanations of algorithms and artificial intelligence often tend to describe them more passively, as methods or objects. As some of the extracts in Table 3 show, explanations use terms such as a ‘way of doing’, ‘ an interdisciplinary science’, or ‘the field devoted to…’. The phrases show that algorithmic systems are often explained as an approach or a discipline, rather than an active entity. This echoes the systemic and assemblage-like conceptions of algorithms discussed above, which are often central to theoretical discussions on algorithms, but are rarely given space in the ways in which users are questioned about their theories on algorithms in participant research.

Comparing these definitions to research on the algorithmic imaginary, we find that the latter tends to inquire about ‘*the*’ algorithm and (echoed in some of our own Google search terms) how ‘*it*’ works; this phrasing runs the risk of framing algorithms and AI as agents or subjects from the offset, effectively filtering imaginaries that might see it otherwise. This may set a precursor for viewing intentionality ascription or anthropomorphism as central to the algorithmic imaginary. The view of algorithms as an agential entity recurs throughout public discourse, but should not necessarily be the baseline assumption for researching the algorithmic imaginary. As Salles, Evers and Farisco (2020) point out, anthropomorphism tends to permeate AI research itself; although they focus on the computer science research context, critical research on AI runs the same risk.

Definitions of algorithms and artificial intelligence found online
"The Instagram algorithm is the heart and brain behind the Instagram app. It decides: - how high your post gets in your followers' feed, - whether your post will be featured on the Explore Page - how many of your followers see your post and - how many users that don't follow you, will see your posts."
"An algorithm is, essentially, a brainless way of doing clever things."
"An **algorithm**, for the non-programmers among us, is a set of instructions that take an input, A, and provide an output, B, that changes the data involved in some way."
"AI is an interdisciplinary science with multiple approaches, but advancements in machine learning and deep learning are creating a paradigm shift in virtually every sector of the tech industry."
"Artificial intelligence (AI) is the simulation of human intelligence processes by machines, especially computer systems.'
"Artificial intelligence (AI) makes it possible for machines to learn from experience, adjust to new inputs and perform human-like tasks. Most AI examples that you hear about today – from chess-playing computers to self-driving cars – rely heavily on deep learning and natural language processing."
"AI is actually a young discipline of about sixty years, which brings together sciences, theories and techniques (including mathematical logic, statistics, probabilities, computational neurobiology and computer science) and whose goal is to achieve the imitation by a machine of the cognitive abilities of a human being."
"Modern AI represents a step into a previously unexplored aspect of human intelligence: the ability to use large amounts of disparate data to arrive at a conclusion that has a high chance of being correct. In other words, the ability to make a guess."
"Artificial intelligence algorithms are designed to make decisions, often using real-time data."
"Artificial intelligence (AI) is the field devoted to building artificial animals (or at least artificial creatures that – in suitable contexts – *appear* to be animals) and, for many, artificial persons (or at least artificial creatures that – in suitable contexts – *appear* to be persons)."
"Learn artificial intelligence by studying natural language processing, reinforcement learning, predictive analytics, deep neural networks, image processing, the human brain, and more today!"

— Table 3: Examples of the different types of definitions through which algorithms and artificial intelligence are explained in Google Search results. —

5.2. Contexts of algorithmic encounters

In order to move away from a focus on 'the' algorithm future research should depart from specific contexts of algorithmic encounters. The topics identified above provide useful pointers to help situate research in a particular domain. Building on the spatial approach taken by Kitchin and Dodge (2011) and the focus on personal experiences stressed by scholars like Bucher (2017), we can infer from these topics the spaces in and through which people encounter and experience algorithms. Nevertheless, as Bishop (2019) highlights individuals have differing levels of engagement, expertise or technical skill in each of these domains. This means that the context of any domain-specific encounter is greatly formative of the imaginaries it might inspire.

Based on the topics identified by our LDA topic model and a horizontal review of the data, we propose a less domain-specific framework for contexts through which people's encounters with algorithms could be studied:

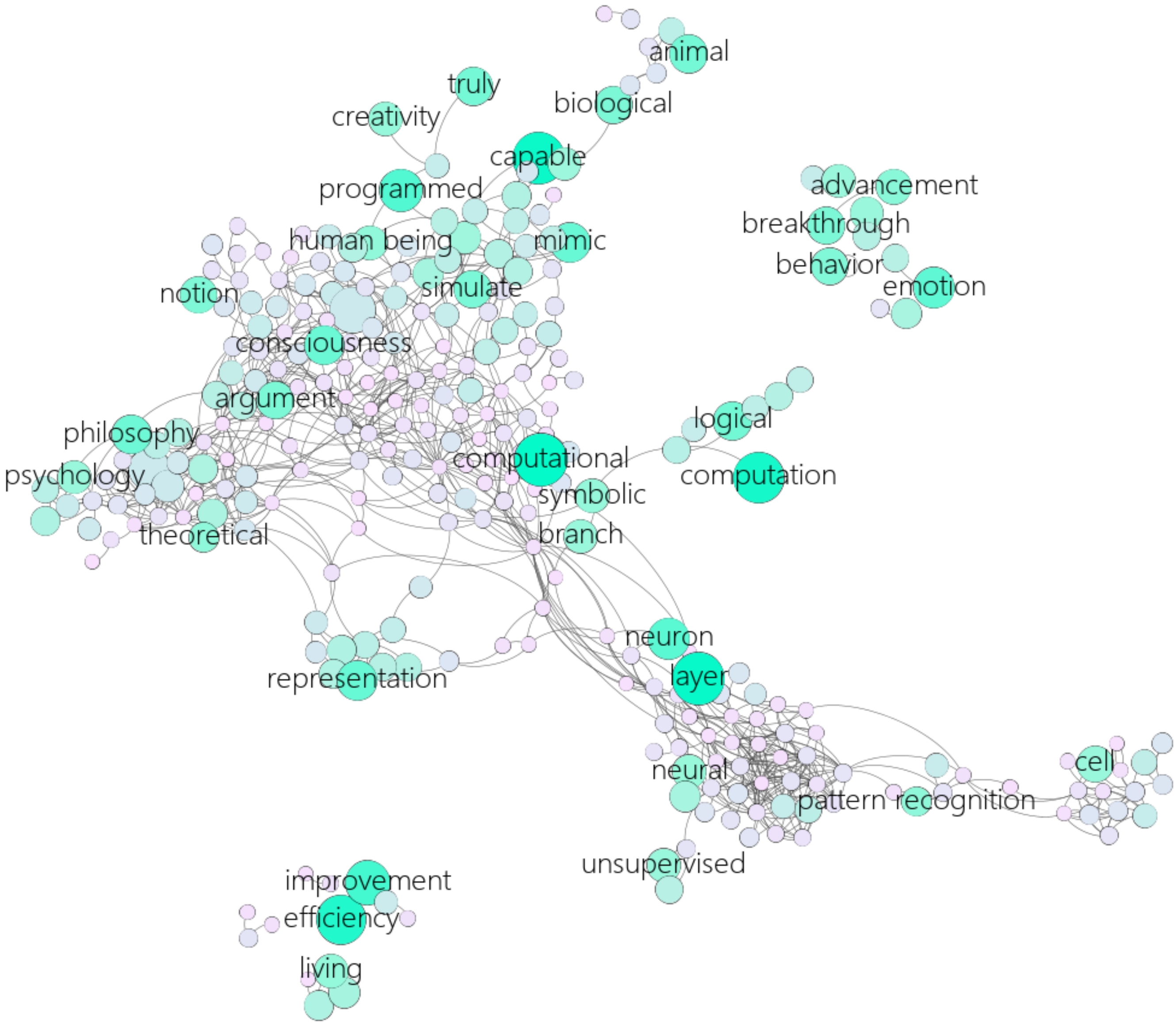
(1) *Work* - at the workplace algorithms assume diverse roles such as tools, co-workers, potential threats, prerequisite knowledge for employment and subsequent career progression, or the products of labour. Algorithmic systems can be both the means and ends of work, often underscored by narratives of automation, optimization and efficiency.
(2) *Leisure and personal interest* - people's free-time is increasingly being spent in the company of algorithms. Whether for entertainment or a deeper sense of self-fulfillment, algorithms permeate pass-time activities like socialising, gameplay, booking gym classes, discovering new music or selecting the next book to read.
(3) *Societal questions and governance* - debates regarding applications of algorithms in public services and questions of governance are widespread and universally relatable. These include arenas like health care, judicial systems or prospects of citizen assessment that touch on people's core concerns.
(4) *Non-digitally-native associations* - algorithms are rarely explained in and of themselves. Outside things and concepts are borrowed to explain algorithmic systems and AI, thereby becoming formative of the systems themselves. This might include for example mathematical operations, cooking recipes, instruction sets, or biological systems; each of these exist independently of algorithms, as well as in conjunction with them.

We suggest that such a framework can be used to identify the contexts in which people encounter algorithms, so as to explore the algorithmic imaginary from a wider, more inclusive perspective. Our findings, such as the distance between the individual topics, as summarised in Figure 2, allow us to abstract some of these wider contexts; the topics 'Social media' and 'Gameplay & strategy' for instance occupy the space in the lower left quadrant, both of which fall primarily into the context of leisure. In addition, the topics identified by our LDA topic model can be useful in specifying a particular domain, prevalent in public discourses on algorithms and AI, within a given context; for example 'Gameplay and strategy' experienced as a leisurely activity, or 'Software engineering' practiced as work.

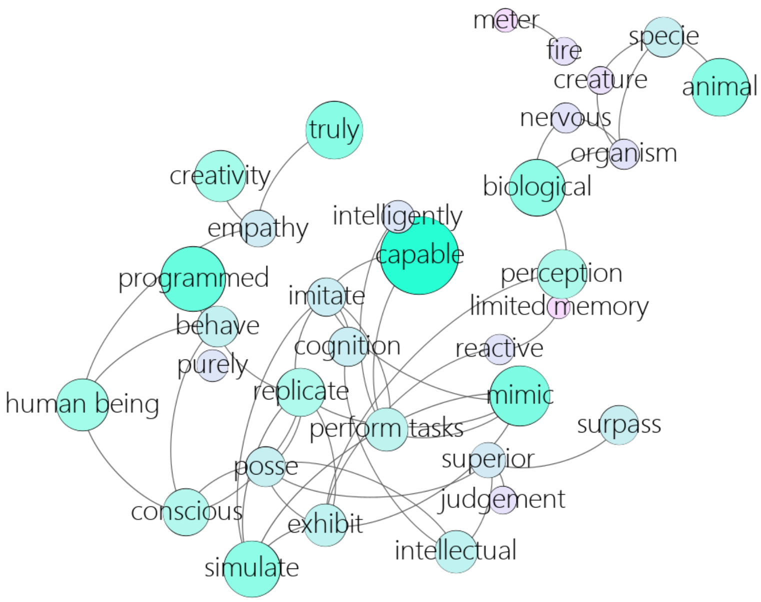
6. Thinking machines and Machinic thinkers

Considering our focus on spatial and situated encounters with algorithms, the fourth category of our framework, non-digitally-native associations, may come across as the least tangible, or perhaps abstract. In analysing our dataset however, we found that explanations of algorithms regularly borrow from domains beyond the reach of direct interventions of algorithms. Likewise, as people's conceptual models of algorithmic systems are often very limited (Alvarado et al., 2020), borrowing external concepts can be a productive means to a working theory level of understanding.

The 'brain' is one example of a non-digitally-native, but widespread association that we found to be recurrent across text-based explanations of algorithms. Although not immediately situated in spaces mutually constituted by algorithms, concepts like the brain occupy a spatial dimension of their own; the brain in particular can be viewed as an embodied concept that people relate to their own bodies and cognition. In order to explore this example in more detail, we expand on some of the semantic relationships of the term 'brain' in our Word2vec model in this final section. Figures 3 and 4 are network graph visualisations of the terms most closely associated with the 'brain' as modelled by our Word2vec model based on our dataset.



— Figure 3: A network graph based on the word2vec model of the dataset, showing the terms associated with the word 'brain' in the context of explanations of algorithms and artificial intelligence. The graph presents the closest connections between the 60 terms most similar to 'brain' and the 20 terms most similar to each of those 60. The nodes are scaled and colour graded proportionally to each respective terms' frequency across the dataset. —



— Figure 4: A close up of the top segment of the network graph presented in Figure 3, characterised by most frequent terms like 'capable', 'programmed', 'biological', 'mimic' or 'animal'. —

The brain recurs across different topics; as the entity behind a social media platform, the end-goal of technological development, the ultimate biological simulation project or the opponent in a game of Go. The brain is referenced in explanations with varying degrees of anthropomorphism; some accounts attribute brains, or at least brain-like resources, to algorithms directly, while others use brain-related terminology to support non-anthropomorphised explanations. The first two quotes listed in Table 3 can be read as examples of the two ends of this spectrum. Its prevalence suggests that people's understanding of the brain is closely connected with or perhaps even constituent of their imaginaries of algorithms. In other words, this non-digitally-native association plays a role in the algorithmic imaginary.

The brain, understood as a concept, can be explored in the context of sense-making of algorithms and used as an analytical tool of the emergent imaginaries; as Bal and Marx-MacDonald (2002) suggest, concepts are a useful methodological approach in interdisciplinary contexts due to their potential for intersubjectivity. The notion of the brain underlying the diverse explanations of algorithms is shared yet different across them, and can therefore serve as an entry point for discussion about some of these differences; the concept can facilitate encounters. We analysed the interconnections between the individual terms that make up the vocabulary of our Word2vec model as a means of better understanding this aspect of the algorithmic imaginary, the concept of brain itself and the means by which these two constitute one another - circularity is inherent to interconnected concepts (Bal & Marx-MacDonald, 2002).

Terms most similar to 'brain' in texts explaining algorithms and artificial intelligence
'biological', 'neuron', 'nervous', 'mimic', 'neuronal', 'replicate', 'anns', 'organism', 'neural', 'emulate', 'cognition', 'simulate', 'imitate', 'operates', 'creature', 'animal', 'multiple_layers', 'specie', 'imitation', 'mental', 'emulation', 'computation', 'neural_network', 'simulation', 'information_processing', 'capable', 'simulated', 'biology', 'mere', 'insect', 'magnetic', 'cognitive_abilities', 'behave', 'intrinsic', 'neural_net', 'interference', 'contributes', 'exhibit', 'interconnect', 'layer', 'capacity', 'equivalent', 'intuition', 'behaviour', 'intellect', 'albeit', 'consciousness', 'perception', 'similarly', 'mind', 'computer', 'conscious', 'evolution', 'cell', 'perform_tasks', 'nature', 'hidden_layers', 'endanger', 'cybernetics', 'neuroscience'

— Table 4: The 60 terms most similar to the term 'brain' by proximity in the Word2vec model. —

Discourses on algorithms are characterised by a constant tension between the possibility of replication and mere simulation of the brain. As Table 4 shows, terms like ‘mimic’, ‘replicate’, ‘emulate’, ‘simulate’ or ‘imitate’ are among the 15 terms most similar to the term ‘brain’. Figure 4 suggests that through ‘performing tasks’, these terms bridge biological concepts like ‘organism’ or ‘nervous’ with aspects inherent to human beings like being ‘conscious’, ‘creativity’ or ‘empathy’. As concepts borrowed from biology are prevalent in both the general and brain-specific explanations of algorithms, debates on the brain’s artificial replication versus simulation can be seen as one popular public discourse.

The interconnectedness of concepts leads to the convergence of their imaginaries. The brain and debates about biological concepts associated with it are perhaps not only prevalent in public discourses on algorithms, but algorithms simultaneously inform people’s understanding of the brain itself. In other words, artificial intelligence algorithms have become a proxy for understanding how the brain works. In this sense, the grouping of words presented in the graph in Figure 3 can be interpreted as some of the ways in which algorithmic imaginaries shape the imaginary of the brain. Notions like ‘pattern recognition’ or ‘information processing’ constitute images of what the brain does, while features like ‘hidden layers’ describe what we might now perhaps call its “architecture”. The popularity of artificial neural networks in artificial intelligence research that today fuels large-scale projects like ‘Google Brain’ reflect this brain-focused image of algorithmic systems. We therefore propose that it is relevant to study people’s understanding of algorithms not only as it feeds back into algorithmic systems themselves (Gillespie 2014; Rader & Gray, 2015), but also because it concurrently shapes the imaginaries of other interconnected concepts. Endowed with brains, people are thinking machines. These interconnected concepts are often non-digitally-native associations.

7. Conclusion

To date, research on the algorithmic imaginary has focused heavily on people’s encounters with content curation algorithms and recommender systems as a means of accessing the diverse folk theories, myths or gossip that these particular algorithms inspire. We have proposed several directions on which future research in this domain could build in order to go beyond this social media-focused approach. We identified a number of domain-specific topics that offer alternative grounds for encounters accessible to people who do not necessarily have technical and expert knowledge of algorithmic systems, for example Business and management, Information processing and policy or Gameplay and strategy. Next to this, we suggest a framework to situate algorithmic encounters in: (1) work; (2) leisure and personal interest; (3) societal questions and governance; and (4) non-digitally-native associations.

Our study only scrapes the surface in identifying the breadth of topics through which people come to grips with algorithms. The prevalence and ubiquity of algorithmic systems, speaks for the relevance of studying these systems critically across this wide range of domains they permeate. Future research on the algorithmic imaginary should explore its aspects in different contexts with a focus on concrete algorithms or algorithmic systems. In doing so, it is important to keep in mind the interfacing role of encounters between these contexts and the algorithmic imaginary, which we highlighted with Figure 1.

Furthermore, as existing studies demonstrate, focusing on tangible traces of algorithmic work is useful in approaching the algorithmic imaginary. Qualitative approaches and field research drawing on the methods employed in existing social media-focused studies are needed to explore the user beliefs or forms of reverse engineering at play in these contexts. At the same time, we suggest that future work should give room to non-agential conceptions of algorithms and avoid their a priori anthropomorphism; algorithms are often explained as a ‘field’ or ‘way of doing’ rather than an agential entity. Similarly, concepts that are not directly constituted by the interventions of algorithms can be formative of the ways in which people imagine algorithmic entities, processes or systems; we suggest these are equally addressed amidst work on the algorithmic imaginary.

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