“The Beatles with the Lower Score, it Breaks my Heart": Framing a Media Education Response to Datafication and Algorithmic Recommendations in Digital Media Infrastructures.[i]

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Introduction

The digital platforms now mediate most of the actions we take when reading news, watching videos, buying goods, finding ways, chatting people, etc. The growing influence of some, such as Google, Amazon or Facebook, raises both hopes (e.g. freedom, economy, etc.) and concerns (e.g. competition, surveillance, etc.). These tensions propel us to invent better ways to discuss the recent and rapid transformations brought by such platforms. The challenge is, both, to make sense of the main social and technical processes that shape these digital platforms and to design situations in which their consequences become discussible, for anyone concerned. Thus, with the hope of addressing these issues, we sought to bridge recent research led in digital media education, about digital literacy and critical education, as well as in science and technology studies, about engineering practices or digital infrastructures.

We decided to focus on the recommender systems[ii] at the core of most of these digital platforms. They promise to provide, both, a unique algorithmic technique for enabling users to orient themselves amidst the wealth of available information and a unique business strategy to keep users engaged with the platforms’ contents and advertisements. They need to be approached, both, as technical infrastructures, which foster interactions between specific users and specific items, and as media interfaces, which partly automate the editorial process. The tension between, on the one side, the opaqueness of their functioning due to technical complexity and business confidentiality and, on the other side, the significance of these systems for the information we exchange and the actions we take, need public debate. The educational challenge lies in making sense of how these social and technical dimensions mingle.

To address this problem, we devised an educational activity, titled “In the shoes of an algorithm”, that would enable people to understand and critically discuss the problems they thought were raised by *recommender systems*. The pen-and-paper game (or simulation), designed in close collaboration with two media educators, offered participants the opportunity to think and act like an engineer, designing a recommender system and like an algorithm, following the engineers' instructions. The shift in perspective would enable participants, we believed, to better reflect on the socio-technical decisions that shape recommender systems and their experience of them – departing, for instance, from more common understandings of privacy issues or technical progress.

This chapter presents the results of qualitative analyses of the observed and recorded sessions of the educational activity, in order to account for its educational effects on participants. We draw three main conclusions. Firstly, the analysis shows that the activity succeeded in helping participants to articulate important technical features shared by most recommender systems. Secondly, it show how the educational activity succeeded in enabling participants to critically discuss the social values embedded in the technical infrastructures, even sometimes imagining alternative ways. Thirdly, the overall initiative shows the value of experiential learning approaches for bringing participants to reflect, at one and the same time, about their media practice *and* digital infrastructures.

Media Literacy and Digital Infrastructures

The recommender systems, insofar as they provide *"means of representation and communication"* indispensable in our daily lives, may fruitfully be approached as *media* (Buckingham, 2019, p. 14). The concept of media brings to our attention two important dimensions of recommender systems (Anderson & Meyer, 1988). First, it invites us to think about the specific material *and* symbolic systems that are involved in communication processes. In this case, recommender systems may be thought of as systems, made of data and algorithms, which, filtering the information we exchange, contribute to shape our environment. Secondly, it further invites us to consider the actions people engage in when participating in such communication processes. In this case, recommender systems importantly influence the actions we take, from the information we share to the goods we buy. The educational challenge thus becomes one of bringing people to reflect upon how recommender systems influence their media practices.

The media literacy, which media education initiatives usually seek to foster, has traditionally been defined as people's abilities to "access, analyze, and produce information for specific outcomes" (Auferheide, 1993, p. 6). The approach to media literacy education followed here further stresses people' abilities to "share meaning through symbol systems in order to fully participate in society" (Hobbs, 2010, p. 31). Hence, the development of technical competences chiefly interests us insofar as they constitute a prerequisite for developing participants' critical competences: capacities to discuss the roles of media in our lives and to imagine alternative ways of relating to them (Jørgensen & Phillips, 2002; Buckingham, 2019). The educational activity therefore aims at providing participants with conceptual tools that, without turning them into technicians, would enable them to articulate social, technical and informational dimensions necessarily involved in media practices (Fastrez, 2010).

The media education initiative focusing on recommender systems came across two main challenges. Firstly, the development of critical competences requires an educational activity that is open enough to enable participants to share the concerns they experience about recommender systems (see Section 3). Secondly, the development of technical competences requires an educational transaction capable of bringing participants to understand otherwise abstruse technical matters, so as to be able to reflect upon how recommender systems affect media content and practices (Saariketo, 2014). The value of the educational activity lies in its ability to foster a critical discussion enabling participants to relate personal experiences and collective processes along with technical infrastructures and engineering practices (Gray et al., 2018).

The studies on socio-technical systems or infrastructures (Bieker & Pinch, 1987; Star & Ruhleder, 1996) focus not only on the technical features they share, but also on the social and technical processes that determine their design. The literature on recommender systems allowed us to establish a number of features common to most recommender systems (Ricci et al., 2015; Seavers, 2019). Firstly, engineers use *data* for setting recommender systems and for producing actual recommendations. Secondly, engineers design *algorithms* to move from data to rankings so as to foster interactions between users and items. Thirdly, engineers use *metrics* to assess the recommender systems' performances. This challenged us to show how an appropriate level of technical understanding of *data, algorithms* and *metrics* may enable genuine critical discussion.

Data about users (e.g. gender, age, location, etc.), items (e.g. genre, date, producer, etc.) or interactions between users and items (e.g. views, clicks, likes, etc.) are central to most recommender systems. The literature in media education (Pangrazio & Sefton-Green, 2019) has stressed the heuristic value of approaching data as a *text,* a situated collection of symbols that could prompt different "activity and inquiry" from readers. Thus, "data literacy" does not stand so much for capacities to read and write data, but rather for capacities to engage in processes where data plays an important part (Selwyn & Pangrazio 2018; Hardy et al., 2019; Seymoens et al., 2020). In a similar vein, the literature in science and technology studies (Gitelman, 2013; Porter, 2018) approaches *data* as traces that can be interpreted (data necessarily is data *from* something) and manipulated (data necessarily is data *for* something). Here, the educational activity would attempt to bring participants to understand how the data can be used for recommending specific items to specific users.

Algorithms provide engineers with means to turn apparently meaningless inscriptions into valuable information. The detailed computational techniques composing recommender systems cannot be easily conveyed to a general audience – they significantly change from one year to another, or from one system to another, and they mobilise a string of complex computational and statistical operations (e.g. k-nearest neighbour, matrix factorisation, neural networks, etc.). Hence, the educational activity would try to convey a general notion of algorithm, avoiding technical considerations regarding recommender systems (Hill, 2016; Jaton, 2017). In a nutshell: algorithms may be defined as *stabilised* and *formalised* computing techniques that may be recognised in a variety of inscriptions (e.g. descriptions, codes, traces, etc.) and that may be executed by any agent mastering a well-defined set of operations (e.g. reading, writing, adding, etc.). Finally, however, we wanted participants also to imagine how engineers would evaluate the performance of their algorithms.

Metrics provide engineers with ways of assessing the behaviour of their algorithms (Slayton, 2015). The performance of recommender systems is usually evaluated offline by comparing, for each user, the list of predicted interactions (i.e. the list of items with which the user is thought most likely to interact) to the list of observed interactions (i.e. the list of items with which the user has actually been observed to interact). The evaluation essentially rests on metrics: mathematical conventions that enable engineers to measure the difference between predicted and observed interactions (Grosman & Reigeluth, 2019). The recent studies in history and philosophy of quantification has shown that metrics constitute a key site where social and technical norms entangle (Porter, 1993; Desrosières, 1993). Hence, the educational activity would seek to bring participants to explicitly articulate these dimensions, discussing the some of the many ways a recommender system may be evaluated.

This review of media literacy and science and technology studies' literature have helped us to unpack the educational objectives and challenges of an educational activity focusing on recommender systems. The media literacy literature highlighted the need to help learners to articulate the technical, informational and social dimensions of media (Fastrez & De Smedt, 2012; Jacques et al., 2013; Claes & Philippette, 2020). Here, educational objectives essentially lie in equipping participants with an understanding of the socio-technical systems at stake, so that they would become capable of critically discussing and articulating the problems they encounter in their daily media practices. The science and technology literature brought forward practical propositions combining an attention to objects and practices, a focus on data and algorithms, a concern for technical and social values. Here, the educational challenge could be largely addressed by allowing participants to manipulate data, design algorithms and discuss metrics.

Method

A Design Based Approach

The critical approach we adopted towards media education meant we treat participants as equals capable of telling what counts for them as important and capable of suggesting ways of addressing such issues (Rancière, 1983). The inquiry was simultaneously an intervention to enable participants to critically engage with digital platforms, and an investigation about the concrete issues participants experience when interacting with recommender systems. Thus, the educational activity, rather than benumbing participants' capacities with massive technical explanations, would instead seek to construct a problematic situation in which participants, would think like engineers and act like algorithms, in order to become capable of critically discussing some of the issues they experience in their daily interactions with recommender systems (Simondon, 1958).

We consequently adopted a design-based method to construct our educational activity (Cobb et al., 2003; The Design-Based Research Collective, 2003; Barab & Squire, 2004; Wang & Hannafin, 2005; Anderson & Shattuck, 2012; McKenney & Reeves, 2013). The core idea of DBR is to bring researchers and practitioners to "depart from a problem and then pursue both knowledge and interventions that address it" (McKenney & Reeves, 2013, p. 4). Two characteristics mattered. First, the method consists of several iterative steps, comprising several cycles of inventions and revisions (Cobb et al., 2003) that can be described as "research through mistakes" (Anderson & Shattuck, 2012). Secondly, the method explicitly integrates both experts and practitioners in the research team (Cobb et al., 2003).

The educational activity was initially developed in close collaboration with a youth media education organization based in Namur called Action Médias Jeunes. From the start, it was envisaged as a one-off activity the association would offer to school or youth centers. The informal character of the educational initiative, performed in the classroom by non-academic actors, enabled us to escape from the stable didactic objectives or systematic learning evaluations that are often required to structure school curriculum (Jacobi, 2001). The design process comprised two main stages. The first stage (Jacques et al., 2020), sought to develop an engaging discussion and to analyze the problems voiced by participants. The second stage, which we discuss in this chapter, sought to assess the educational outcomes of the final activity.

The Educational Activity

In the Shoes of an Algorithm is a two-hour long pen-and-paper activity, played by around twenty people aged 14 plus. The objectives are to develop a recommendation algorithm, to rank videos, and to evaluate the different recommendation algorithms. During the first phase, participants are divided into three groups. They are expected to act as engineers designing a recommendation algorithm, and as computers executing the designed algorithm. During the second phase, participants are grouped together. They are expected to present and argue about the merits of their respective algorithms and then more generally to discuss and reflect on their media practices.

During the first phase participants act as engineers. Each group receives a data sample about the videos to recommend, and need to devise a calculation rule general enough to enable them to rank the videos. The second step requires participants to act as algorithms. Each group receives, at regular intervals, new data that needs to be quickly processed, following the devised calculation rule, to produce actual recommendations. The participants are given limited instruction on how to proceed and are encouraged to collectively address possibilities and obstacles.

During the second phase, the teams discuss and evaluate their algorithms. Participants first present their own algorithm explaining their respective calculation rules and, finally, the groups vote on the most convincing recommendation algorithm. Then the media educator steps in, acting as a Chief Technology Officer, offering participants to evaluate, for them, their respective algorithms as most digital platforms would. Finally, the participants more broadly discuss the challenges encountered in the course of the activity, their own experiences of digital platforms, and the importance of recommendation in forming cultural habits.

Analyzing the educational outcomes of the game

In the shoes of an algorithm essentially rests on an experiential learning process based on the participants' experience (*knowing how*) rather than an explicit and theoretical learning process (*knowing that*) based on the professors' knowledge. Knowledge thus emerges in the interplay between the learners' own experiences and expectations. The task of an educator is consequently redefined, not so much as introducing participants to technical knowledge, but rather as creating problematic situations within which participants are invited to transform their own knowledge.

As noted, the educational activity aims to enable participants to better think and talk about recommender systems (Gray, 2018). Learning may be thought to take place each time tensions between the participants' experience and expectation may be observed (Kolb, 1984). The triggers, indicating such tensions, may be (1) resorting to one's own experience (e.g. an intimate or a second-hand knowledge of the platform) to address a broader issue, (2) encountering an *obstacle* (e.g. a discrepancy between expected results and those produced by the algorithm) that propels an invention, (3) vivid argument about the decisions that are to be taken (e.g. from the more relevant data to the more desirable objective). These triggers acted as markers of where and when learning might take place.

The data used in our analysis essentially consists of partial transcriptions of two sessions from the nine sessions we attended. Each session comprised: one hour per group designing and executing an algorithm; and, for the second phase, one hour where all the groups discussed together. The first session (ESC) gathered sixteen years old students from the same class of a Belgian secondary school. The second session (CDS) gathered twenty years old students enrolled in the second year at a Belgian University. The remaining sessions comprised further sessions with secondary school students, university students, and with university researchers and administrative staff. The following section analyzes long and continuous extract of the sessions so as to render the participants' critical reasonings.

Results

During the first phase of the activity, small groups were invited to get acquainted with the data they received, to devise their own ranking procedures, and to process the provided data. The educators went from group to group: complementing the instructions received, helping them to overcome difficulties or, sometimes, challenging them. The interactions between participants often took the form of questions regarding the relevance of the data (e.g. I believe *this* number means *that*), arguments about the design of their ranking algorithm (e.g. Should we not change *this* weight?) and exchanges related to actual computations (e.g. Tell me the value of *this* cell). A few interactions also supported casual discussions about musical taste (e.g. I don't like *this* music!) or each other (e.g. I know him since kindergarten!). The next four sections systematically analyze the interactions surrounding data, algorithms and computations.

The second phase of the activity consisted of one large group debating the relative merits of the various data and algorithms presented. It discussed recommendation processes and personal tastes, argued about the issues raised by recommender systems and digital platforms. The educators here led the discussion through rather open questions (e.g. Can you think about examples of other recommender systems?), or picking up on a question or a comment expressed by a participant (e.g. Do you agree with *this* idea?). The discussions, taking place in a larger group, adopted a more formal tone in which participants would account for the design choices they made, argue about the relative merits of different data and algorithms, or exchange their views of digital platforms. The final three subsections here analyze the interactions about algorithms and the digital platforms.

Grasping Data

Participants begin by discussing the *data* they received. Analysis of the sessions uncovered three broad gestures traditionally associated with data literacy. First, participants sought to *contextualize* the data at hand, by considering its limits. Second, participants attempted to collectively *interpret* the data, by discussing the charts' readings and relating them to their experience. Third, participants sought to *extrapolate*, from the sample they received, to other data they might come across. The following extract usefully condenses these otherwise sparse forms of reasoning. The discussion here took place between participants discovering the data we provided to them: namely, demographic data about videos (to be ranked) and demographic data about a persona (for which they must be ranked).

First, participants contrast the data currently available (i.e. gender, age, location) with other data, assumed to be available (i.e. user history):

> *– Lisa: So, the elements composing the formula must be found in the data they give us?*
> *– Ismael: Yes, it seems.*
> *– Lisa: Because her browsing history, for example, might also be very useful. Let us imagine she watches influencers' videos, but her twin sister watches wrestling videos, the suggestions won't be the same, but the formula must remain the same.*
>
> *[ESC, User Data, 1/3]*

Secondly, participants discuss what should the correct reading of the chart be, invoking their personal relation to the data presented.

> *– Yan: Here they give us an example: 'J'ai tout oublié' by Angèle is listened more often by men, living in France, aged between 13 and 17.*
> *– Lisa: Really?*
> *– Ismael: No, by women.*
> *– Fanny: Hmm, so Yan does not know how to read a chart.*
> *– Luke: Indeed, it is more often listened to by women, living in France.*
>
> *[ESC, User Data, 2/3]*

Third, a participant bluntly rejects an interpretative use of the personal relation one might have to the data.

> *– Yan: Whatever, I listen to Angèle, and last time I checked, I was a man.*
> *– Lisa: And? Is the chart based on you?".*
>
> *[ESC, User Data, 3/3]*

Interpreting Data

Participants then further explored the significance of the data, interrogating the social processes from which data might have been generated; and secondly, considering the relevance of the data for particular tasks. As well as instantiating the two relations one can develop to data (data *from* processes and data *for* tasks), the following extract shows how key collective discussions are to a robust interpretation of data. This discussion took place some time after they have received their data dealing with statistics about videos (views, likes, comments, etc.) and channels (subscription, progression, etc.).

First, participants questioned the relevance of some data (i.e. comments, subscribers, views, etc.) by questioning their possible meanings (e.g. comments may be considered as positive or negative interactions, or yet as mere reactions).

> *– Nils: Guys, we have forgotten the comments.*
> *– Frances: Yes, but that's a choice. Personally, I find comments obsolete.*
> *– Moussa: Yes, one can have 450 thousand positive comments or 450 thousand negative comments.*
> *– Tim: Nonetheless, it shows the popularity, because if people react, it means that it is relevant.*
>
> *[CDS, Video Data, 1/3]*

Participants discussed the relevance of data in relation to their still undefined objectives, aligned with their knowledge about how Youtube functions (i.e. rewarding videos with comments) or with other possible ways of functioning.

> *– Mona: Actually, one earns more money if there are more comments.*
> *– Frances: After all, we are not forced to make like YouTube [...] we are not forced to copy Youtube's policy.*
> *– Jerry: Shall we vote on who wants to take comments into account? For me they have no value.*
>
> *[CDS, Video Data, 2/3]*

The discussion shows an essential role of argument in the process of forging a robust interpretation of the data at hand (e.g. data may be meaningless, evidence for positive interactions, information about people's attention, etc.)

> *– Frances: The number of views could do, but the number of comments? anybody can say anything.*
> *– Tim: It shows that followers are engaged and active.*
> *– Mona: It shows that the video has caught people's attention, positively or negatively.*

– Nils: So, shall we take them into account?”

[CDS, Video Data, 3/3]

Designing Algorithms

Participants had to invent a rule for ranking the videos received. They envisioned which kinds of operations might allow them to pass from data to rankings. Participants usually encountered two kinds of obstacles. Firstly, they might struggle to agree on what should be considered when recommending videos (What to discard? How to weigh? etc.). Secondly, they might have difficulties stabilizing the operations that should produce recommendations – note that the structures of their algorithm may significantly vary with the kinds of data groups received (e.g. one-line formula, hierarchical trees, vernacular procedure, etc.). In the following extract, participants manipulating demographic data, assisted by the educator, overcome difficulties to agree upon what should be taken into account as it was turned into a stable series of operations.

After a struggle with the diversity of possible algorithmic design and the necessity of stopping one calculation rule participants were asked about the relative importance of the kinds of data (here: gender, age, and location) and about the objective of the recommender systems (here: music or tutorials).

– Educator: So, do you take gender into consideration? Not location?
– Emily: We only take the age in consideration. Gender is not relevant for music. Although, it might well be for tutorials ...
– Carl: And the location is useless.
– Hind: How do you deal with Chinese videos that have millions of views, then?
– Carl: Maybe some people watch them, location is not relevant.
– Educator: It is up to you. You need to understand that there are no good or bad answers. It is up to you to decide the formula that you find the most interesting.
– Emily: So for instance, the percentage associated with the age (13-17 years old, in the case Juliette) more the percentage associated with the location (here: Belgium).
– Educator: That is one way of doing it.

[ECS, Demographic Data, 1/2]

The discussion shows participants hesitating as to whether the envisioned procedure is general enough so that it can be used to recommend any video (here: Angèle) to any profile (here: Juliette) – a concern pervasive in computing practices.

– Arnold: But how to do that in mathematics?
– Emily: What?

– Arnold: You cannot do it in English.
– Emily: In which language do you want to do it, then?
– Arnold: In mathematical language. Here you only calculate one thing. We need to make a global procedure that could work on all kinds of songs.
– Educator: And this is not good?
– Arnold: It only works for 'Angèle'.
– Emily: One just has to replace.
– Educator: She wrote in English 'Each time we have a video, we add the percentage of people that have the same age and the percentage of people that live in the same place as Juliette ... that is a way of formalizing, one can apply it to any video.

[ECS, Demographic Data, 2/2]

Executing Computations

Finally, we invited participants to act as algorithms, having to process the data they received every five minutes or so, according to the algorithm they had just designed. The participants may face unforeseen cases, having to adjust the computational rules (e.g. when a ties happen between videos). They may be disappointed by their rankings (e.g. "The Beatles with the lower score, it breaks my heart") or realize the algorithm they designed happens to be too demanding in terms of computational time. In some cases, the participants even divided the computational labor – this requires a rule that can easily be broken down and supposes an equal involvement among participants. Hence, algorithms appeared not so much as formal disembodied entities, but as concrete operational processes, whose executions and results generally need to be assessed by trial and error.

Presenting Algorithms

The general discussion held at the end of the game systematically started with a quick round, during which teams presented each other, the data they had received and the algorithm they designed. The presentation demanded participants explicitly articulate a variety of dimensions: contrasting the material they received, justifying the data they considered relevant, explaining the rules and objectives their algorithm embedded, and summarizing any computational difficulties. In the following extract, one student presents the algorithm his group designed, after having introduced the data they were provided (views, likes, subscribers, etc.):

— Tom: First, we took the 'number of views of the channel' and we divided it by the 'number of views of the video'. We obtained a number and divided it by 10, to have a score on 10 [...] Then we took the 'likes of the video' and we subtracted the 'dislikes' from the 'likes'. It gave us an average, roughly, of what people liked [...] it allowed us to see whether or not a video was liked or disliked

by Youtube users. Then we took the 'number of views of the video' and the age of the video and we divided the 'number of views of the video' by the 'number of months of the videos', so that we got an average of the number of views per month. And after, each time, we took the averages on 10 of the three computations I just described, and we did an average of the three, to rank the videos.

[CDS, Discussion 1/2]

The public exercise required them to produce an intelligible description of the algorithm's functioning, and to provide reasons that might ground the choices they made during the engineering phase (e.g. relating bits of the formula to social processes). They also had to recognize imperfections that might hamper their algorithms (e.g. the gap between aims and achievement). The teams' performances inevitably varied. The following passage, taken from a group manipulating demographic data (i.e. gender, age, location), shows one example of the difficulties sometimes encountered when accounting for calculation rules:

– Mary: I will explain little by little… What we did is that we started from 15... and we always multiply 15 by 0, ½, 1 depending on the location, if it is respected. So, for the location we gave: 15 times 0 if it was 'Other' the higher, 15 time ½ if it was countries speaking English and 1 if it was countries speaking French, so we started with 15 times 0, ½ or 1.
– Educator: So, you rewarded the video when the video was often watched in the same geographical zone as the person.
– Mary: Yes, that is it.

[CDS, Discussion, 2/2]

Evaluating Algorithms

The educators then invited participants to contrast the algorithms designed by the different teams and to then rank the algorithms they found the most relevant. The discussions generally focused, on the kinds of data provided (and the power of generalization presumably associated with them) — and less, on specific algorithms that had been presented. Interestingly enough, participants often changed their positions in the course of the discussion (e.g., it would often take some time before participants realized the interest of viewing histories for recommending). In the debate transcribed below, participants argue about the capacities of data and algorithms while discussing their representations of users' preferences or engineers' objectives, and oppose ideas about how alternative recommender systems might work.

Participants first discuss the relative merits of different recommender systems: arguing about the relevance of the data or the tension between personal and impersonal recommendations.

– Educator: Does someone have opinions about which algorithms are more or less important?
– Oliver: They all are important.
– Amelia: Some focus too narrowly on specific users, so they might not be general enough.
– Noah: For me it is the opposite, some people like and dislike videos without really thinking about it: there may be haters or fake accounts. We could base our recommender system on the age of people having actually watched the videos, it remains general enough.
– Zoe: But the problem with the data on age (and all) is that it is based on past data, of people having watched the videos, while here we have the rest of the data (likes, dislikes, etc.)

[ESC, Discussion 1/3]

Participants then discussed the various objectives the recommender system may need to consider. They mobilize, in the course of the argument, their own preferences, representations of users' wants or assumptions about YouTube's goals.

– Jack: Personally, when I am on Youtube, the videos I want to see are videos close to the videos I usually watch and, sure, to have some novelty, but not too much.
– Mia: This is rather subjective. Some prefer targeted videos. Others not.

[ESC, Discussion 2/3]

These participants, we contend, gradually learn to think more like engineers, and to be able to critically reflect about the social consequences of the choices they made, sometimes even proposing alternatative recommender systems to overcome some of the limits perceived (here: the possibility to choose the configuration of the recommender systems).

– Mia: Maybe we should allow both.
– Educator: So, users could choose?
– Mia: Yes. [...]
– Henry: It also depends if we want to please the public or the company.
– Educator: How?
– Henry: If we give what the public wants, we will necessarily receive more money than if we give them something they may not want to watch.

[ESC, Discussion 3/3]

The educator would then close this part of the debate by asking participants to vote for the algorithms they find the most relevant and by placing an insert on how

YouTube's Chief Technical Officer might have evaluated their algorithms – unpacking an intuitive case of metrics.

Discussing Recommendations

The discussion process would then allow participants to recount their own experience and discuss wider societal challenges. All participants related mixed experiences about YouTube's recommender system and they appeared keen to blame recommender systems. For example, recommendations were charged for being off mark by a student: "sometimes, I seek to watch similar videos and it'll just won't come up with anything interesting" [ESC, Discussion]. Another student accused them of locking him in: "for instance, if one listens to a rap song, it will only propose rap songs, but we might well wish to listen to something else: it locks us into a musical genre we already have" [CDS, Discussion]. They insisted on the interest of that recommender systems that enabled the discovery of songs – and how they relied on them. Some participants also seemed to place conflicting expectations on recommender systems: "I want something out of the ordinary, not necessarily something known, not necessarily popular, that I am sure I will like because I behave like a lemming, I also want to get less known songs" [CDS, Discussion].

The participants sometimes succeed in moving from personal frictions to more general issues raised by recommender systems. Thus, the very personal sensation of being enclosed in a bubble is sometimes turned into a broader political argument about recommender systems producing uniformity: "We will shape people as we want them to be… we will lead everybody to the same things… everybody will like the same things… eventually, people will have less personality" [ESC, Discussion]. The systems were accused of perpetuating the established order: "Before saying criteria such as gender, age, etc. are important, one must first see the cultural and social contexts… and then: Do we decide to perpetuate a gendered culture? or Do we decide, with our algorithm, to break up these habits" [CDS, Discussion]. The emerging ability of participants to move from personal experience to more general accounts of recommender systems provided the basis for a collective and critical discussion.

Criticizing Platforms

The discussion finally brought participants to situate recommender systems within digital platforms and to imagine alternative ways of conceiving of them. The participants appeared to resort to three main arguments for better situating recommender systems within digital platforms. First, they sometimes proposed to articulate their experience being captured by the recommender system's objectives: "The objective is that we stay on Youtube [...] their objective is that it pleases us, so we are willing to watch" [CDS, Discussion]. Secondly, participants often sought to articulate their second-hand knowledge about influencers' money-making practices in terms of assumptions about the platforms' strategy: "I have seen an influencer saying it: the longer the video is, the more advertisement can be displayed, and the more money can be made" [ESC, Discussion]. Third, they sometimes attempted to relate processes across several platforms: "When we do search on Google, we have suggestions, I wonder: Is that an algorithm? Thus, it is not uniquely relevant what we see on Youtube, but also whatever we see on other websites." [CDS, Discussion] Hence, participants shared and enriched their knowledge of the dynamics in contemporary digital platforms.

The participants systematically sought to conceive alternative recommender systems. They often wanted to take into account features, subtler than the ones available to them or to Youtube's engineers: "It would be interesting to develop a program that would analyze the comments" [ESC, Discussion]. They also imagined platforms that could let people choose between the different systems: "Ideally, we should be able to choose the kind of recommendation we want, whether we want to have recommendations that are diverse or similar to our tastes" [CDS, Discussion]. They proposed, although more rarely, recommender systems that could work on different grounds: "The movie critic recommends based on her expertise, the critic says, without knowing us, I find this movie is good for this and that reason… while Youtube does this on the basis of probabilities" [CDS, Discussion]. The educational activity appears to have stimulated an appetite for alternative recommender systems.

Discussion

The following sections respectively address two main main questions. Firstly: What did the participants effectively learn? Secondly:What limits and perspectives does this educational activity raise?

Learning Outcomes

The analysis shows that our educational activity gave participants an opportunity to improve their capacities to think and talk about recommender systems. From a technical perspective, the educational activity would generally open up with participants' fuzzy answers to the educators' opening question "What is an algorithm?" Nevertheless, the activity required participants to invent a sound way of turning a set of data about videos into a list ranking the videos, and seemed to have invariably brought them to articulate elementary technical capacities, at the core of algorithmic practices, as described in the first half of the preceding section: manipulating personal data, formalizing ranking operations, and dividing computational labor. The fictional situation inviting participants to act, in turn, as Youtube engineers and algorithms, enabled participants to acquire an understanding of algorithms as creations of situated engineers, rather than disembodied technical processes. Thus, participants were gradually brought to apprehend the social dimensions of these technical operations. The educational activity made recommender systems collectively discussible.

The activity and the exchange proved instrumental in bringing participants to discuss recommender systems critically. From a critical perspective, the educational activity allowed us to document three of the many sense-making strategies deployed by participants towards recommender systems. Firstly, through an enlargement of perspectives: moving from particular experience to more general considerations (e.g. from influencers' monetization to Youtube's policies). Secondly, as the statement of a concern: turning a social experience into a political injustice (e.g. from pleasing recommendations to establishing order). And finally, with the imagination of other propositions : from the actual system to an alternative one (e.g. from an imposed to a chosen environment). The educational activity, we thus suggest, does indeed foster critical engagement with recommender systems in particular and digital platforms in general.

Our analysis shows how participants were brought to approach data and algorithms as design engineers as well as everyday consumers. This enabled participants to articulate technical constraints (e.g. data availability, mathematical formalization, calculation complexity, etc.) and social objectives (e.g. advertisement money, user engagement, recommendation diversity, etc.). It imposed us to neatly circumscribe the technical dimensions of these media technologies, which often preempt educational activities at the expense of other more critical dimensions. The activity not only provides participants with the means to understand how data and algorithms might be involved in recommender systems but, more significantly we hope, left them with an understanding of how, through metrics, engineering practices embed social objectives into socio-technical systems. Thus, the educational activity appears to have succeeded in treating the technical competences, not so much as *ends* for the activity, but rather as *means* for enabling participants to exert critical competence.

Limits and Perspectives

The emphasis of Fastrez (2010) on the social, informal and technical competences characterizing media literacy enabled us to more finely place the outcomes of our educational activity. While the activity undoubtedly fostered the articulation of the technical and social dimensions of recommender systems, it left relatively untouched the informational dimension (e.g. the interface of recommender systems or the effects of platforms' algorithms on their contents). The technical dimensions of recommender systems had to be limited, leaving important aspects outside the scope of the educational activity (e.g. the processing capacities and the learning algorithms are patently absent). The discussion of the social dimensions may have been limited by the very nature of the informational content staged during the activity. Music videos, ensure participants' early engagement, but unlike News for example, may well hamper a more substantial discussion about recommender systems consequences.

The educational activity wagered that the learning would prove more effective by immersing participants in a game-like simulation. The educators, acting as Youtube's Chief Technology Officers, invited participants to act, in turn, as engineers and as algorithms. It incorporated a plausible role-play dimension by creating a playful ambiance, using time limited elements in the activity to create a rhythm and by designating a winner in the classroom. The engagement of participants remained, overall, a success, although it strongly varied with group dynamics. However, the immersive character of the activity appeared to sometimes neglect the passage from doing to saying (e.g. skillful students would often publicly present). Further work might uncover neater ways of articulating the game-like activity to more formal educational setups.

Thus, for instance, the interpretive method used for assessing the educational outcomes of the activity, which largely stemmed from our critical stance and our experiential approach, cannot easily be articulated to more traditional forms of assessments used in formal education. However, the results here presented might be read as providing indications as to how formal education could take advantage of the informal activity, namely: by proceeding to a more traditional lecture (and evaluation) on data and algorithms and by designing a collective or individual exercise allowing professors to evaluate participants' arguments. These developments, on which we are currently working, shall enable us to more tightly relate the informal educational activity to more formal educational stakes.

Conclusion

We aimed to design an activity that would help us address the tension, experienced by many people, between a digital platform's significance and its opaqueness (the "black box"). The educational activity sought to improve participants' capacities to think and talk about recommender systems – also, providing them with the technical capabilities to engage a discussion about these matters. The game-like simulation confronted participants to an open problem impelling them to come up with a rule for passing from a set of personal data about interactions between YouTube's users and videos (inputs) to a list of ranked videos that might stand as YouTube's recommendation (outputs). They were brought to act, in turn, as engineers designing the algorithm and as computers executing the designed algorithm.

This chapter has addressed the effectiveness of our intervention by analyzing recorded sessions from the educational activity. The analysis looked for triggers where the technical and critical enter the discourse. During its first phase, the activity brought participants to better grasp the concept of data with increasing precision, and to articulate computational rules and recommendation objectives, to better envision the ranking effects of their computational rules. During its second phase, the activity allowed participants to move from a specific to a general experience, to assess the fairness of a computational rule and to imagine alternative ways of recommending. The educational activity, we believe to have shown, succeeded in creating a space in which participants become capable of critically reflecting upon recommender systems as well as digital platforms.

We further hope the activity and our analysis of the results may inform other media education initiatives that take digital infrastructures as their object. In terms of content, the educational activity sought to set a fruitful balance between enabling participants to make sense of rather complex technical infrastructures, while leaving enough room to critically discuss how such infrastructures affect their media practice. In terms of method, the simulation invited them to penetrate inside the algorithms' manufacture, bringing them to approach otherwise abstruse technical devices as concrete processes mingling social and technical dimensions (e.g. filters, business, tastes). The experiential approach enabled participants to articulate their concrete media practices in more abstract discussions. This balance and our experiential stance appeared to be key in designing an educational initiative that fostered technical and critical competences.

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[ii] We prefer this terms as used by the engineering community (see, for example the ACM conference) as opposed to the more common phrase recommendation system.