Acting on Data. Temporality and Self-Evaluation in Social Media

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Introduction

This paper contends that one of the key contemporary forms of valuation and measurement is self-evaluation. It takes self-evaluation in social media as the empirical focus and introduces to a number of services that allow users to make sense of the data they produce on social media platforms. While users perform increasing amounts of activities and connections, platforms offer only limited possibilities to make sense of one's own data and often turn activities into fleeting objects on streams and promote immediate interaction without organised access to the past (Berry, 2011; Gehl, 2011). Such a lack has opened up the opportunity for a number of third party self-evaluation applications to emerge.

The primary interest of the paper lies in the performative capacities of self-evaluation devices. It suggests that the forms of reactivity and self-fulfilling prophecy that have commonly been identified as a problem in some forms of measurement (Power, 1997; Espeland and Sauder, 2007) are actually an intentional effect of the calculations supported by these tools. That is, the measurements they produce are not designed to capture a separate reality, but rather function as framing devices, inviting some types of engagement and action while ruling out others. Yet, so it will be argued, the capacity to evaluate and modify the self afforded by the tools is tied up with the agency and (self-)evaluation of the tools themselves.

There are two intermediate layers to this argument. First, I investigate such framing dynamics by focusing on the production of numbers in such tools as, to use Helen Verran's term (2009), specific kinds of enumerated entities. The term draws attention to how numbers are never simply abstractions, but always have an impact on the users they evaluate. To explore the role of numbers as participating in practices of self-evaluation, I engage with questions of mediation and the role of medium-specificity as developed by Richard Rogers (2009; 2012). Self-evaluative tools draw on data and activities specific to social media platforms, and bring them into new relations through processes of enumeration. Second, I question the production of particular temporalities both in social media platforms and in associated self-evaluation devices. This allows me to show how tools for self-evaluation at the same time operate within but also expand the temporalities afforded by platforms, by creating selected access to the past while constantly directing attention to potential futures through the production and presentation of numbers. Again, medium-specificity is crucial to questions of temporality, as the reorganisation of activities and data specific to platforms also reconfigures their temporalities. The interlinked movement of numbers, media and users in self-evaluation can thus be seen as a kind of dynamic assemblage, one that allows to open up multiple evaluative criteria and creates, so my argument, multiple temporalities.

The temporalities of social media

Engaging in social media means producing data through activities allowed by platforms, such as tweets, status updates, likes, comments, bookmarks, retweets or replies. The facilitation of user activities, content cross-syndication and connections between users and digital objects are key characteristics of the social web (Appelquist et al., 2010; Langlois et al., 2009). Yet, only the platforms have complete and ordered access to the data produced in such activities and facilitate in motion elaborate data mining and evaluation infrastructures in the back end (Elmer, 2004), while users only get limited access to their data. In the case of Facebook and Twitter, user data is mainly featured in the form of chronological streams, as sparse aggregations of contacts or actions performed or as selected clusters of grouped actions. Instead, these platforms provide elaborate devices to notify users about the responses their activities generate among other users, such as Facebook's notification flag and pop-up notifications or Twitters announcement of new tweets and new responses.

The absence of organised data access and the difficulty of retrospective engagement, paired with the centrality of streams in such platforms creates a spacio-temporality of immediacy and priviledges real time engagement, so Robert Gehl argues (2011). Following O'Reilly (2007), web 2.0 but especially social media platforms create infrastructures in which users are asked to continually add value by building content, creating connections, hence turning platforms into ever changing spaces. This ongoing engagement, Gehl continues, is based on immediacy and speed, on rendering sharing, liking and tweeting easier and increasing the pace of social interaction through immediate notification devices: "The emphasis on the new in Web 2.0 leads to immediate affective exchanges; I email you, you chat with me. If you do not, I become anxious" (Gehl, 2011: 7). This particularly applies to platforms operating with streams, in which new content, produced by users or cross-syndicated from other sources, is instantly displayed in real time and in reverse chronological order and notification objects draw attention to new content or new interactions (Berry, 2011). The temporality of such streams has been understood as immediacy or now-ness (Lee and Liebenau, 2000), creating the same time for all web users: "Internet Time is absolute time for everybody. Now is now and the same time for all people and places. Later is the same subsequent period for everybody. The numbers are the same for all" (Lee and Liebenau, 2000: 140). Instead of engaging in such flattening account of real time, the paper seeks to question the centrality of this "now" by investigating how platforms and self-evaluation tools create their own medium-specific temporality, emerging from an interplay between pasts and futures whilst connected to processes of numbering and calculation.

Besides real time, streams are further character ised by their continuity; following Berry (2011) they are designed to differ and to remain constantly incomplete (see also: Knorr-Cetina, 2005). The infrastructures of platforms not only encourage users to respond now, like now, tweet now and share now, but also to like again, share again and tweet again. The limited time span of the now is therewith extended and gains duration and continuity: "Here the present is perceived in the future on which it encroaches, rather than being seized in itself" (Bergson, 1991: 927). Or to put it with Gehl: "This dual reliance upon user-generated 'newness' and the emphasis on always-becoming are built into the architecture of Web 2.0" (2011: 6). Such continuous immediacy in the front end of platforms is complemented with extensive data mining in the back end of social media platforms, a process in which each activity can produce potentially multiple elements of data. "For every explicit action of a user", Berry argues (2011: 152), "there are probably 100+ implicit data points from usage; whether that is a page visit, a scroll etc.". It is the constant, immediate user interaction that allows to fill the associated databases or archives with ever new data points, contributing to a constant interplay between "'real time drives' and the archival impulse" (Gehl, 2011: 6) and the emergence of a two-fold temporality of social media platforms.

Mapping the field

A series of third party providers have seized the lack of platforms to allow users to systematically access their past data to develop a range of tools that present and pattern personal user data for individual sense making. Rather than providing a complete overview of this growing field, I discuss a range of key approaches how such tools reorganise user data, drawing particular attention to the use of numbers. The majority of existing devices have at their core the creation of numbers based on the simple addition of activities and/or connection predefined by associated platforms. Yet, the tools further process these aggregates through various kinds of calculations, which, even at the most basic level, make use of different temporal intervals or comparisons to other users as referent populations, and are typically also combined with additional information from metadata, such as timestamps or location based data.

Tweetstats[1], for instance, a platform for Twitter statistics, visualises user activity over time, producing curves of tweet activity of the last month, aggregates of tweets according to weekdays or hours during the day and offers a calculation of the user's percentage of replies and retweets. Additionally, the service offers a number of tag cloud visualisations depicting most used hashtags, @reply recipients and used key words to account for the topics addressed by the user. Like Tweetstats, the majority of self-evaluating devices draw on activities that themselves materialise as activities pre-structured through medium-specific features of platforms such as tweets, retweets and replies on Twitter, comments, wall-posts and likes on Facebook or +1s and comments on Google+. They pose medium-specific possibilities to perform activities that at the same time allow the production,

[1] http://tweetstats.com/

engagement and analysis of data. But whilst platform interfaces pose one form of enabling and organising such activities, self-evaluation devices allow for new differentiations of form.

A similar approach to the aggregation of individual user activities is adopted by the Facebook application Status Statistics[2], which, once a user has granted it access to private profile data, counts status updates, provides figures on average word counts and frequency of update postings related to daily and hourly intervals. Other devices - such as TwentyFeet[3] and Tweetreach[4] - use aggregations to explore relations between users, networks of connectivity and reach of activities. TwentyFeet describes itself as an "ego-tracking device"; it monitors the number of platform connections and transforms aggregated user activities into curves that show changes in their frequency over time. The device presents its statistics according to as qualitative measures, such as "Reputation Indicators", "Influence Indicators" and "Conversation" but the data displayed is based on a mere aggregation - the conversational index for instance refers to likes and comments on Facebook versus retweets and replies on Twitter. But Twentyfeet also offers a further set of 'predictive' numbers for expected responses and changes in friend/follower counts through the use of the technique of extrapolation. These predictions are emailed to users weekly and previous predictions are compared to the actual figures for purposes of evaluation: "Your response rate changed slightly/noteworthy".

The use of predictive calculations and the comparison of user activities with their predictive metrics creates for users a climate of future orientation and alertness to maintain ongoing interactions with other users. In creating these climates of anticipation, the provided numbers or metrics are turned into scores since it is in relation to these numbers that users are inclined (literally positioned on a curve), with the implicit invitation to at the very least maintain their level of activity if not to increase it. A series of tools offer further calculations designed to support users to maintain their activity level. Crowdbooster[5], for instance, makes use of an alternative mode of visualisation: it depicts the response rate to tweets by turning individual tweets into bubbles on a grid, indicating the number of retweets and the number of potential impressions of each tweet on the axis. This presentation of data allows users to follow which tweets resonate more and which less, offering information relevant to the improvement of response rates through strategic posts.

On top of calculative techniques of aggregation, ratio (proportional comparison) and extrapolation, a number of self-evaluating tools also draw on proprietary algorithms, the precise details of which are kept hidden. Especially metrics of influence draw on non-disclosed algorithms to calculate users' presumed reputation. Among the most used of such services are Klout[6] (which is

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[2] http://apps.facebook.com/status-statistics/

[3] http://www.twentyfeet.com/

[4] http://tweetreach.com/

[5] http://crowdbooster.com/

[6] http://klout.com/

disused in greater detail below) and Kred[7]. The later provides users with a general Kred score between 1-1000 and an unlimited outreach or exposure rank, both related to the social media platforms users decide to connect to the service. In contrast to other tools, which only take users' online activities into account, Kred allows to implement offline achievements to complement its influence calculation, including university degrees, frequent flyer status or memberships in accredited clubs. The tool also features rankings of most influential users in different topic categories and offers users 'fresh' content based on their previous activities and preferences, with the objective to assist users to increase their scores through strategic network building and topic engagement.

PeerIndex[8] also offers a general influence score between 0-100, paired with three sub-metrics, but puts special emphasis on topic engagement with its Topic Fingerprint grid. Twitalyzer[9] shows its own score next to a user's Klout and Kred score and offers six complementary metrics, namely engagement, influence, clout, generosity (the number of retweets), velocity or frequency and signal, the use of URLs, hashtags and mentions in tweets. This breakdown correlates with the different aggregates that feed into its own impact metric. It thus makes visible the categories of its calculation, whilst keeping the actual algorithm undisclosed.

A further category of self-evaluation devices enables the user to create and showcase 'collections' of their own data. Facebook for instance introduced the option to download one's profile in 2010, providing users with a zip-archive of all data visible on their profile page, including all wall activities, pictures, events, notes and maps. The data comes in HTML format and can be queried and processed further. Yet, the downloadable information is limited to what is already visible on a user's profile, while data relating to activities performed and content shared outside the profile, for instance by posting on a friend's wall, sharing a video in a group or creating an event in the past are not included. Twitter on the other hand, provides a more complete access to one's data set on request, featuring all Twitter activities and full user analytics.

Similarly, the web service Archivedbook[10], which offers an interface to explore one's profile history, is also limited to what is already visible on the actual profile. But unlike on Facebook, status updates, wall posts, events, check-ins, links and pictures can be sorted according to multiple criteria such as newest/oldest first and most commented and most liked. This sorting feature allows users to navigate and sort their own data in new ways, but does not offer any additional aggregates, comparisons or calculative functions. A different dataset is being archived by Likejournal[11], a service that seeks to repurpose the content sharing possibilities of Facebook's like and share button to turn them into a social bookmaking service with which users can store and organise their shared objects.

[7] http://kred.ly/

[8] http://www.peerindex.com/

[9] http://twitalyzer.com/

[10] http://archivedbook.com/

[11] http://www.likejournal.com/

On Likejournal, users can also follow other people's liking activities, creating a social networking platform based on the data produced within another platform.

Beyond turning activities, likes and tweets into numbers and curves, a further group of services focuses on network and graph visualisation. Among this category are some of the most used self-evaluation applications for Facebook, such as Touchgraph[12] and Friendwheel[13]. The majority of network visualisation apps follow a graph approach, turning contacts into nodes and creating connections or edges based on friendship or other criteria, often also clustering the connections according to location or networks. Many graph visualisation apps put special emphasis on pictures and offer photo-based networks, following the assumption that the co-presence of users in the same photo is an indicator of a close relation. Tools like Vasande Visualiser[14] offer a filter to sort such graphs based on profile information such as male/female or single/in a relationship, enabling new forms to navigate one's Facebook connections. The Facebook Social Graph[15] application also offers a so called popularity score, which turns a user's position in a network into a number on a rank - without providing much background information about the ranking process. Similar services are available for Twitter, such as Mentionmap[16], a tool that maps connections based on interactivity, assigning common topics to interacting users.

A final cluster of tools includes devices for curation and storification. They are fairly rudimentary, but they assist users to navigate streams and allow them to store and organise fleeting content. The idea of storification, the clustering of streams into topics as 'stories' also informs Facebook's Timeline.[17] One of the best-known services is Paper.li[18] for Twitter which automatically turns followed tweets referring to predefined topics into a newspaper format, notifying the users whose tweets are featured in the paper. Keepstream[19] on the other hand focuses on saving tweets based on topics, hashtags or lists in order to publish them on blogs or personal websites - combining archivation with curation. Storification of one's own tweets is possible with Twylah[20], which automatically detects topics, sorts tweets into clusters and displays them in a Tumblr inspired format with the objective of making tweets available with a wider public that is not active on Twitter. Other

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[12] http://www.touchgraph.com/facebook

[13] http://apps.facebook.com/friendwheel/

[14] http://vansande.org/facebook/visualiser

[15] http://apps.facebook.com/socgraph/

[16] http://mentionmapp.com

[17] Before the introduction of the Facebook Timeline at the end of 2011, individual user profile walls used to be organised as ephemeral streams of activities in reverse chronological order. The recently introduced Timeline is based on ideas of life-story-telling and self-curation, so Facebook claims, and provides monthly and annual summaries and clusters of connected activities, such as new friends, liked Pages or received posts.

[18] http://paper.li/

[19] http://keepstream.com

[20] http://www.twylah.com

storification tools such as Trunk.ly[21] and Storify[22] focus on the networking aspect and enable users to build communities based on their activities in Twitter outside of Twitter.

To sum up, acting both as filters and as navigation devices, all these tools build on top of data produced within platforms and variously use counts, comparison, ratio, algorithms, graphs or network visualisations, as well as the clustering of topics to offer a different experience of data than the one offered by platforms.

Ranking influence: The Klout Score

Klout, a metric of influence founded in 2008, is taken as the key case for further analysis here as it is probably the most used (as well as being probably the most criticised) tool for self-evaluation.[23] The services strives to be the "standard of influence", where influence is defined as the "ability to drive action" (Klout, 2012). Its particular use of numerical metrics, algorithms, ratio and other comparisons enables to raise questions about the role of numbers in social media in general and in the production of relations between platforms, users and temporalities in particular.

Klout comprises a general Klout score, three sub-scores, topic lists per user and a social media usage typology, visualised as style grid. To get a measure of their influence, Klout users can integrate their activities from a large and growing number of platforms, including Facebook, Twitter, Linkedin, LastFM, Foursquare, and others. Based on their interactions in these platforms, each user is assigned a Klout score between 1-100. This score is itself a combination of three sub-metrics, measuring reach, amplification and the user's network. Overall, the tool focuses on interactivity, rather than mere activity, evaluating how many inter-actors a users' actions are exposed to (in the so called TrueReach sub-metric), their ability to generate responses in their networks (Amplification) and the quality of the networks of responding contacts (Network Impact).

For all its calculations of influence, Klout draws on responses that themselves materialise as activities pre-structured through medium-specific features of platforms such as tweets, retweets and replies on Twitter, comments, wall-posts and likes on Facebook or comments, re-shares and +1s on Google+ (Klout, 2012). It is the process of enumeration, that is the transformation of activities into numbers, that allows Klout to compare an @reply on Twitter with a comment on Facebook. To create these numbers Klout has built a relational database, in which each user's activity is turned into a number of data points, complemented by data points within their network. These data points and their relations do not add up to either a single individual or a whole population, but are designed to remain open, to be constantly added to and enter new relations, which Klout seeks to stabilise temporality into metrics of individual influence.

[21] http://trunk.ly/

[22] http://storify.com/

[23] For an overview of influence tracking services, see Storm 2011.

To address these multiple relations and their temporal stabilisations further, the work of mediation might be of interest, as it is inextricably part of the process of enumeration, since it is the medium-specific activities that allow for both numbering and relating. Elena Esposito (2004) addresses this issue by reference to Luhmann's distinction of medium/form, drawing attention to the granular elements of a medium which take on different forms in response to the relations created between them. As she puts it, in relation to the medium of language: "The elements are the single words that in the medium have no connection to one another and gain sense only in the context of the sentences coupling them tighter" (Esposito, 2004). In the case of the social media, the elements are likes, shares, retweets etc, which are, in the operations of search, sort, store, share, count and algorithmic processing brought into multiple and dynamic relations which each other, leading to medium-specific forms of ranking. While social media platforms open up one way of organising these parts, focusing on immediacy, tools for self-evaluation offer alternative formations.

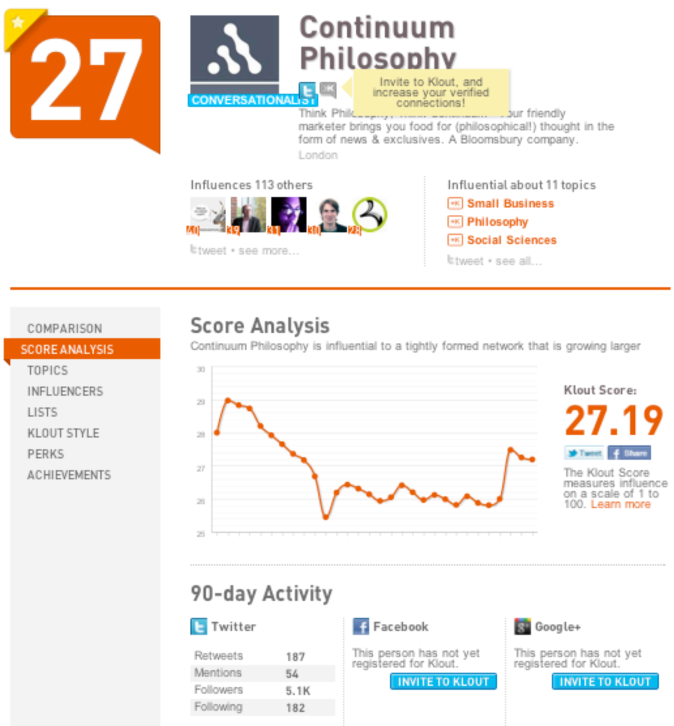

Image 1 : Klout Score Analysis.

To explore the relations between both data points and users, lets have a closer look at the Klout rank itself, which assigns each user a single number in the range of 1-100. It is this single number score that can be used as the basis of self-evaluation through comparison, both in regard to other users or temporally, through the comparison with previous scores. How such comparisons operate becomes apparent when looking at this enumerated entity in relation to the mathematical concept of ordinality. Deploying a ranking between 1-100, Klout contains influence to an ordered position within a finite set of ordinal numbers, that is, setting up a sequential ordering of discrete elements. As Alain Badiou puts it: "(i)n the ordinal view, number is thought as a link in a chain, it is an element of a total order" (2008: 31). Despite being ordered alongside a chain between 1-100, the position of a user in this chain is not fixed, but subject to an ongoing process of real time and relational calculation. Each score is dependent on the continuous production of responses and the networks of the respondents, leading to the fact that Klout automatically calculates the Klout score of a users' network, implementing data of users who do not know that they contribute to Klout's database. The role of rankings and associated calculations has recently become subject to sociological and cultural discussion of measurement and numeracy (Guyer, 2010; Verran, 2009; Espeland and Sauder, 2007), addressing their socio-economic impacts. In her discussion of the significance of rankings, Jane Guyer (2010) reflects on how ordinality creates both relations but also competition between the ranked entities by drawing on the notion of schizmogenesis, a term she takes from Gregory Bateson. She writes:

> "Between moments when the process stops for the ratings to move in, all participants relate to one another continuously and competitively. The results seem very close to what Bateson (1958[1936]) called 'schizmogenesis': the continual reproduction, confirmation and intensification of difference, which is then ritually marked when the process itself is momentarily suspended, as if for collective contemplation and affirmation." (Guyer, 2010: 4)

In Guyer's terms, the numbers produced by Klout as individual scores feed a ranking that simultaneously creates relations of equality and difference between social media users, connecting them to each other as influencers, whilst demarcating differences by locating them in relation to each other on a competitive score. Rendering influence as a position in an ordinal sequence creates it as an entity that can potentially decrease and increase, as each score is only a temporary fixation and also related to the achievements of other users. But, while such ordinal rank might suggest that change in influence is only possible as two-directional movement, in which the rank can go up or decrease, such one-dimensional change is complicated when looking at the intervals between the discrete ranks and the other metrics Klout offers.

An inexact, yet rigorous order

The fact that the ordinal set is limited between 1-100 might suggest that each rank is defined by its distance from start and end-point and that the distances between ranks form discrete, uniform steps. But this is not the case. The Klout score operates in a way that the distances grow exponentially the higher the position on the rank. Klout itself observes: "The average Klout Score is not 50; instead, it is around 20. The Score becomes exponentially harder to increase as you move up the scale. For instance, it is much harder to move from a 70 to a 75 than from a 20 to a 25" (Klout, 2012).

From a mathematical point of view this, however, does not mean that the number is not supported by a system of distributed and well-ordered value in which "every link of the chain follows ('follows' meaning: comes just after in relation of total order) only one other, [and is] well determined (it is the minimal element of what remains)" (Badiou, 2008: 53). Key to many ordinal chains are the non-uniform yet rigorously defined ‘distances’ or ‘intervals’ between each step – more particularly, it is the distinctive interplay between these steps in the Klout rank that creates relations and differences between users. The form of exponential ordinality emerging in the case of Klout is not uncommon in contemporary rankings, as Guyer observes: “In many cases, intervals diminish radically going down the scale, both in real terms and in proportion to their next positions” (Guyer, 2010: 3). In Klout’s ordinal scale, intervals are not only exponentially ordered but they are also constantly altering, stretching and bending, according to changing proprietary algorithms and transformations in user activities. Klout reworks its algorithmic calculation on an ongoing basis and at points alters its algorithm and therewith user scores fundamentally.[24] 100 is therewith not an absolute, external best, but a relative better, demarcating the best performance so far – and is currently being occupied by a teenage pop singer. Should a different user achieve even better, the algorithm would reconfigure the rank’s distribution. A user’s achievement is therewith connected to the achievements of the referent population of all Klout users. Klout has created a ranking system that does not refer to an absolute, external and standardised measure - despite its ambitions to be the “standard of influence”. Rather it is designed as dynamic and relational metric in which individual achievement is connected to the achievements of other users and cannot be situated in relation to external measures.

The implication of such relational measurement is, to draw on Manuel DeLanda, that ordinal series such as the Klout score “behave more like topological spaces, where we can rigorously establish that a point is nearby another, but not by exactly how much (given that their separation might be stretched or compressed)” (2002: 82). As a consequence, comparison and orientation becomes difficult, if not impossible, from the outside but only allows to make sense from the inside, through engaging, playing or experimenting with the numbers. The topological space of evaluation created by Klout is not defined by one middle value - organised through a mode, median and mean - but offers multiple dimensions of orientation, multiple ways to relate to other users and to act upon data.

Such multiple dimensions of orientation from the inside emerge from the presentation of the main score and its sub features, relating users to different referent populations and different temporal intervals. First, the Klout algorithm draws upon a population of users that is not closed, but is rather constantly changing both in magnitude, and in its internal relations. While the overall Klout score calculates a user’s influence in relation to the achievements of all other Klout users, the Klout style grid positions users only together with the people they influence, opening up a different referent population. Second, the social media style grid sorts users and their influencers into clusters organised alongside criteria such as focused vs. broad, casual vs. consistent etc (image 2). While the ordinal rank only opens up a bi-directional movement, as the Klout score can get higher or lower, the grid allows

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[24] This relational and experimental character of the algorithm became visible when Klout changed its algorithm in October 2011, a decision which resulted into significant changes in user scores. The sudden drop of scores among very active social media users led to a widespread discussion of the use and value of influence rankings and a critical Twitter campaign against Klout. This flexibility of relations is most interesting in the context of Klout claiming to be the “standard of influence”, whilst the standardisation of the algorithm is itself still in the making, revealing how the proclaimed standard is a provisional and experimental one.

for multi-directional movement. The grid spectrum is demarcated by the passive position of the "Observer" and the active and highly influential "Celebrity". In between the grid offers a range of differentiated clusters, such as the "Specialist", characterised by focused and consistent engagement in a delineated topic area, or the "Conversationalist", opening up multiple directions of orientation and movement.

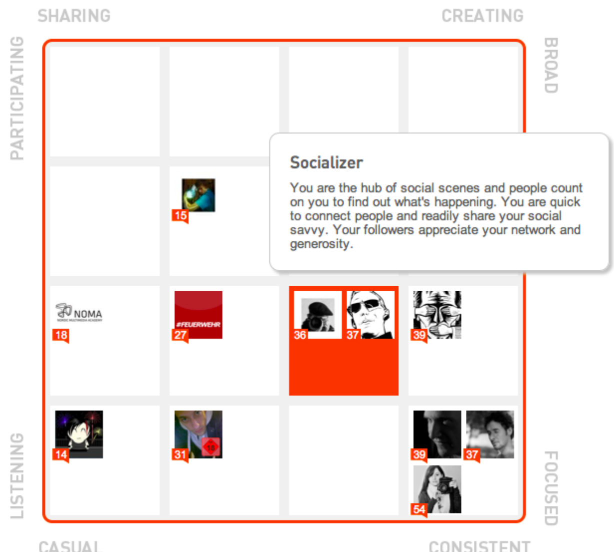

Image 2: Klout Style grid.

Third, the three sub-scores are not presented as limited ordinal series but appear to have an infinite range, with no upper limit. It is impossible to establish a centralised measure in relation to the sub-scores and making the limits invisible or doing without limits at all, Klout explicitly introduces a space in which orientation becomes difficult and merely focused on 'achieving better'. Finally, Klout makes an effort to constantly draw user attention to the volatility of their score. Despite the prominence of the single number of the main rank, a series of elements on the Klout website focus on visualising the non-fixity of the rank, informing the user of any increase or decrease in their score. The rank and its sub-scores are presented as curves, come with several tendency indictors which show how the ranks have changed in relation to different temporal intervals (image 3) and are complemented with a set of notifications that flag out the most significant changes at each login. Such features highlight that the 'current' score evidently only poses a temporary fixation. An interesting folding of temporalities emerges, relating a score to multiple intervals of the past to create alertness for its potential future development - which in the end feeds back to the climates of immediacy created by the platforms, as users are encouraged to interact constantly and instantly in the present to maintain or improve a given score.

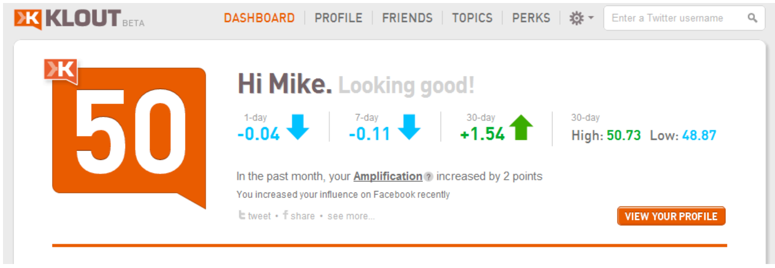

Image 3: Klout dashboard and notifications.

Let me now link the making of multiple dimensions of orientation and avenues to act upon data back to the operations of mediation and explore how social media self-evaluation has turned into a site of capitalist frenzy. The production of the Klout scores and its various other metrics is the outcome of a series of real time calculations happening in Klout's relational database. The Klout algorithm disaggregates the data retrieved from platforms, detaches it from individual users and transforms activities into numbers to create comparability between them. Each of the deployed metrics involves a series of calculations, which allow the initial data – the number of tweets, shares or likes - to enter new relations. By putting the data into new relations and comparing the results with the performance of other users, the algorithm reassembles the data into the Klout rank and its sub-ranks and brings the ongoing relation making and calculation process to a momentary stabilisation.

In such process of disaggregation and reaggregation, it is not the individual user that matters to Klout's relational database, it is the decomposition and recomposition of data points which fosters the possibility of creating unbounded relations between data points and thus opens up avenues for valorisation (Latour, 2012). This claim can be exemplified by turning to Adrian Mackenzie's work on relational databases, who remarks in reference to Alan Badiou: "No-one belongs to a database as an element, but many aspects of contemporary lives are included as parts of databases" (Mackenzie, 2012: 12). While these parts, the data points Klout reaggregates, do not sum up to a single total or whole, they can create an excess of inclusion over belonging and can create ever more relations. And it is this excess that is the source of contemporary forms of value, and is of interest both inside and outside the economy. Value thus lies not in the detached agency of an individual user, but in the creation of new modes of coupling between data points that open up possible frames for action, personalised advertising and recommendation cultures.

Finally, the question of who can realise this value and how is obviously important. Whilst users can retrace certain numbers that feed into the score, the relations Klout creates between the parts remain opaque as part of its proprietary algorithm. This nondisclosure, while it may annoy some users, may also serve to motivate other users to include ever more data, to connect to more platforms, hoping that the provision of more activities will benefit their score.[25] Klout connects its score to the provision of ever more data from different platforms, a practice that has, not surprisingly, drawn

[25] The non-disclosure of the algorithm also prevents users from hacking the system and developing networks of mutual interactivity to increase their score, the service argues (Klout, 2012).

criticism: “This linkage fundamentally undermines the quality of the service. In effect, Klout pays you to endorse its service by rewarding you with a higher rank” (Gilin, 2011). But such a criticism fails to understand that Klout is not a measure from the outside, but from the inside. In its ongoing and relational calculation, which is based on the inflow of ever new data points, the Klout database is characterised by its incompleteness and invites users to participate by providing more data. Klout score does not pose a descriptive metric, it works as a productive entity or inventive frontier to speak with Helen Verran (2009), co-producing what it attempts to measure. And this co-production is precisely what feeds its own ability to drive action.

Despite receiving multiple criticisms,[26] the Klout rank has been incorporated by a growing number of companies and is informing a series of business practices. Social media clients like Hootsuite, Seesmic and CoTweet have implemented Klout scores in their dashboards, allowing users to filter and sort social media contacts according to their Klout score (Berry, 2010). Klout scores are also being implemented in customer relationship management systems, for instance by Salesforce.com and Radian 6, which use the scores to decide how fast to respond to customer requests, giving consideration to potential positive or negative sentiment the given customer can generate in social media (Vaughan-Nichols, 2011). Just as Klout understands the influence of individuals as the “ability to drive action”, it makes an effort to drive its own action, by convincing users that its algorithm is trustworthy so that they provide more data and by utilising their users’ ability to drive action to advance their own influence on cooperating partners.

Reworking temporalities

In a final step, the paper returns to questions of temporality emerging in the context of self-evaluation tools. Platforms, so I have argued at the beginning of the paper, are characterised by an interplay of immediacy as presented to users, whilst creating archives in which the past of the network is only accessible to platform owners. Self-evaluating media such as Klout intervene in, but also reinforce this temporal configuration. The Klout score, the sub-scores, style grid and their presentation enable a particular form of engagement with one’s past activities by relating them to different temporal intervals. But creating such selected visibility of one’s past data at the same time exposes the volatility of a user’s current rank and draws attention to its future in which the rank might potentially decrease but ideally should stabilise if not increase. The Klout interface is populated by multiple reminders that each rank is only a temporal stabilisation and might lower if users do not maintain their level interactivity. The so called Score Analysis page for instance features four curves, for each rank and sub-rank, complemented with tendency indicators (image 1). The start page

[26] Since its launch in 2008, Klout has been object of repeated critque: mostly regarding its attempt to ‘quantify’ influence and reputation, but also for its introduction of competition and hierarchies to social media which once had been imagined as flat and egalitarian; for focusing on online activities only, neglecting any influence derived from offline activities; for turning social media engagement into self-branding; and finally for the opaqueness of its algorithm which claims to be a standard but rather is privisional and work-in-progress (Gillin, 2011).

summarises the most noteworthy changes and demarcates the highest and lowest score of the last month, introducing yet another temporal interval. The multiplicity of such intervals, curves and indicators, even though posing fixed numbers, animate the score and create alertness for its potential change. The extension into the past provided by Klout does not so much encourage a retrospective analysis, but suggests to focus on the future and to continue one's social media engagement.

A number of media theorists have recently engaged in the discussion of futurity as central to the temporal dimensions of new media in general and social media in particular (Grusin, 2010; Berry, 2011; Elmer and Opel, 2008). Richard Grusin (2010) reflects on the role of contemporary media as the pre-emptive remediation of the yet-to-come, the creation of an anticipatory readiness for a particular future, opposed to the reworking of past media formats or immediacy as suggested in his seminal account of remediation. The reconfiguration of temporalities premediation seeks to describe is especially at work in social media, so Grusin, constituting an anticipatory readiness and expectation of ongoing interaction and situating the temporality of platforms both in the present and in the future.[27] Using social media hence comes with the expectation of interaction and responsivity: "Social networks exist for the purpose of premediating connectivity, by promoting an anticipation that a connection will be made – that somebody will comment on your blog or your Facebook profile or respond to your Tweet" (Grusin, 2010: 128). This expectation comes with an associated thread of potential disconnection or terminated interaction, as expressed by Gehl (2011). By showing users how their activities are taken up and resonate among their contacts, the Klout rank contributes to the production of such worlds of alertness, anticipation and thread of disconnection. Just like platforms and their notification systems, Klout sets up social media engagement as immediate but continuing activity, and turns likes, shares, tweets and status updates into anticipatory gestures which are expected to be met by another gesture. Interestingly, it is not the content of the anticipated interaction which matters in this climate of alertness and evaluation; it is the event of the interaction itself.

Klout thus opens up the temporality provided by platforms into two directions, towards the past and towards an anticipation of the future. But therewith the score does not introduce an alternative and more open temporality than the platforms themselves, because this reconfiguration contributes to the platform's facilitation of ongoing, immediate interaction. Focusing users on the constant evaluation of their so called influence fuels a climate in which users feel prompted to respond to platform activities, immediately and in real time, to maintain or increase their given ranking.

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[27] Grusin compares the pre-structuring capacities of premediation with those of a computer game which does not prescribe users what to do, but creates worlds and framing devices with render some actions more likely than others: "Premediation would in some sense transform the world into a video or computer game, which only permits certain moves depending on where the player is in the space of the game, how far advanced she is in achieving the goal of the game, or the attributes of her avatar. Although within these premediated moves there are a seemingly infinite number of different possibilities available, only some of those possibilities are encouraged by the protocols and reward systems built into the game." (Grusin, 2010: 46)

Self-evaluation and recommendation

The temporal dynamics and processes of enumeration therewith benefit the associated social media platforms, but they are also essential to Klout's very own revenue model. As a service offered for free to users, Klout generates its financial revenue through the processing and re-selling of access to user data, for instance through its Perk system. Perks are free or reduced products, services or test experiences provided by third party companies which are offered to Klout users who have a particular score and are active in related topic areas. Such perks come with no obligations and are presented to users as gifts rather than as objects of exchange. But given the case that users decide to talk about and even recommend their Perks, their remarks may generate debates valuable to the cooperating partner, so Klout suggests: "Perks are distributed to select influencers based on their topics of authority, location and score. If you influence your friends on the topics that you care about, then chances are high that a company in that industry wants your opinion" (Klout, 2012). The disaggregation and reaggregation of user data allows Klout to match the interests and assumed impact of social media users with those of cooperating partners. That is, users with a high score and influence in the category of automobiles might, for instance, be offered a free test drive, based on the anticipation that this experience will translate into recommendations in social media, which are then supposed to influence a further car interested population. Via Klout, corporations can address a highly specialised and presumably influential audience and in the case of users discussing their received Perks, retain insights and create word of mouth effects. The Perk system can be understood as an attempt to monetise the creation of climates of anticipation, more precisely the expectation that the activities of a particularly ranked user will have an impact on the user's network. Moreover, while companies anticipate user engagement with Perks, the possibility to be rewarded with Perks further motivates users to maintain their score and provide Klout with more data, to achieve more free Perks.

The calculative processes involved in the pairing of users with high scores and selected interests with free product offers can be understood as particular form of recommendation culture. To speak with Ganeale Langlois et al. "personalized recommendation is the result of the algorithmic processing of a user's profile correlated with other profiles and potentially commercial interests" (2009). Devices for recommendation in social media, so Pariser (2011) suggests, operate by folding past and future, strategically exposing social media users to content, activities and offers based on their or their contacts' past actions in order to achieve engagement with recommended content in the future. Yet, the recommendations Klout offers are different from the algorithmic preselection of content, which creates encapsulations or filter bubbles related to users' presumed interest fields, such as the personalisation of Google results or the organisation of Facebook's News Feed (Pariser, 2011). Whilst Google and Facebook deploy algorithmic filters to prestructure access to information, Klout Perks deploy user activities themselves. They require the active engagement of users to complete the process of recommendation. In this case, the presumed filter bubble is not a default setting, but coproduced with users themselves, who decide to engage with Perks and by talking about them, bring into being a user generated recommendation culture.

Conclusion

The paper has engaged with Klout focusing on the interplay between numbering, mediation and evaluation, giving consideration to how the evaluation of users is closely tied up with the evaluation of the tool itself. The paper explored how the Klout score emerges as the outcome of constant disaggregation and reaggregation of data produced though activities specific to social media platforms and offers alternative mediations and temporalities of the same activities than the ones provided by the platforms. Klout presents its score as limited, ordinal set and visualises user achievements in relation to a series of temporal intervals. Doing so, the self-evaluation tool supports sense making of one's data in the past, but also directs attention to potential future changes in the score. Hence, what is being disaggregated and reaggregated are not only data points related to users, but also temporalities.

Different than social media platforms, devices for self-evaluation do not focus their users on immediacy, but support an orientation towards the future and its curation. They provide a different temporality than the platforms themselves, yet contribute to the dynamics of immediate interaction by adding continuity to real time platform engagement, as users are alerted to maintain their interactivity in order to maintain their scores. The time Klout opens up and aims to define with its Perk system and with its entire interface is the time before real time, before immediate interaction. To put it with Berry: "The best thing is to anticipate its arrival, its 'realisation' before it gets there. That's money on credit. It's time stocked up, ready to spend, before real time. You gain time, you borrow it" (2011: 162). Real time platform interactions are thus connected to what precedes them and what will follow them. To focus users on the nowness of interaction, platforms need a complementary interest in the future, which is, so the paper suggests, offered by self-evaluative media. A folded account of time emerges in the context of social media self-evaluation, as addressed by Bergson: "Here the present is perceived in the future on which it encroaches, rather than being seized in itself" (1991: 927). To relate such considerations back to practices of numbering, I have argued that Klout's ordinal rank contributes to emergent forms of social ordering from the inside, in which the achievement of a user is connected to and dependent upon the achievement of other users. The Klout rank so moves beyond a mere descriptive metric or numbered number, to speak with Deleuze and Guattari (2004), it is neither fixed nor disentangled from the activities it measures. Instead it creates a numbering number, which is not external to what it seeks to describe, but actually contributes to the production of influence. Deleuze and Guattari understand numbering numbers as numbers in movement, produced through changing activities, relational calculations and altering modes of measurement. In the case of Klout, such numbering numbers not only bring themselves, but also social media users into movement as framing devices, inviting users to care for the future of their score by constant engagement with social media in the present.

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