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Computing the Everyday: Social Media as Data Platforms

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Abstract
We conceive social media platforms as socio-technical entities that variously shape user platform involvement and participation. Such shaping develops along three fundamental data operations that we subsume under the terms of encoding, aggregation and computation. Encoding entails the engineering of user platform participation along narrow and standardized activity types (e.g. tagging, liking, sharing, following). This heavily scripted platform participation serves as the basis for the procurement of discrete and calculable data tokens that are possible to aggregate and, subsequently, compute in a variety of ways. We expose these operations by investigating a social media platform for shopping. We contribute to the current debate on social media and digital platforms by describing social media as post transactional spaces that are predominantly concerned with charting and profiling the online predispositions, habits and opinions of their user base. Such an orientation sets social media platforms apart from other forms of mediating online interaction. In social media, we claim, platform participation is driven towards an endless online conversation that delivers the data footprint through which a computed sociality is made the source of value creation and monetization.

Key words: Classification, Categories, Social Data, Sociality, Social Interaction, Social Media Platforms, Post-transactional spaces

Introduction: Platform Participation

Social media platforms are by now integral to contemporary society. In the course of roughly a decade they have grown to important means through which the Web is accessed, and through which social relationships are sought and built online and beyond. This in many ways remarkable penetration of the social fabric by social media has gone in tandem with the increasing significance social media organizations have assumed for the wider digital economy. Not surprisingly, these social and economic developments have given rise to a growing and diversified research agenda on the topic. The initial focus and understanding of social media as networking sites (Baym

2010; boyd and Ellison 2008; Baym; Kaplan and Haenlein 2010; Papacharissi 2010)[1] have gradually been complemented by several other approaches that have sought to document the structural and technological complexity of social media, and the critical role they play in contemporary economy and society (see e.g. Bucher 2012, 2015; Elmer, Langlois and Redden 2015; Gerlitz and Helmond 2013; Van Dijck 2013).

An important implication of this growing and diversified research portfolio is the recent shift to understanding social media as platforms (Gillespie 2010; Helmond 2015; Van Dijck 2013). There are several strong undertones the concept carries including those of complexity (differentiation of components and their links) and evolvability (Baldwin and Woodard 2009). The concept has, no doubt, been used with different meaning across such diverse fields as industrial economics, design science, sociology and information systems (Baldwin and Clark 2000; Bowker 2005; Gawer 2009; Hanseth 2000; Sørensen, De Reuver and Basole 2015). But it seems to us that a common theme underlying the approach to social media as platforms is the delineation of the role platforms assume in shaping the communication and interaction fabric of everyday life. It is against this backdrop that social media platforms are seen as not neutral to user platform engagement. Rather, platform user engagement and networking are considered as being mediated, or *plat-formed* to deploy a neologism, by the conventions, design choices and instrumentalities of social media technologies, and the socio-economic context in which social media *qua* organizations are operating.

Building on and extending such scholarship, this paper focuses on key aspects of the infrastructural, backstage datawork of social media platforms. By unveiling the standardized and quantified models on the basis of which social media orchestrate user platform participation we intend to account for the infrastructuring role social media platforms assume in the re-making of everyday. We synthesize several theoretical currents and draw on our ethnographic involvement with a social media platform for shopping to expose central practices and data-based techniques through which social media engineer user platform participation. The data thus procured are variously deployed to sustain online sociality and to trade the outcome of user engagement (more data) to advertisers, data analytics companies and other platform stakeholders. Our aim is to produce a portrait of social media that contemplates the technological underpinnings of these platforms and links technology to institutions (Kallinikos, Hasselbladh and Marton 2013). Social media platforms, we claim, are ultimately data-based organizations that extract value and make profit from the social everyday they themselves engineer.

We also contribute to the literature on social media by shifting the focus from the significance frequently attributed to algorithms (e.g. Beer 2009; Bucher 2012; Cheney-Lippold 2011; Gillespie 2014; Orlikowski and Scott 2014; Pasquale 2015) to the backstage datawork through which data are standardized, tided and made algorithmic

[1] In their seminal contribution, boyd and Ellison referred to social media platforms as social networking sites and defined them as: “web-based services that allow individuals to (1) construct a public or semi-public profile within a bounded system, (2) articulate a list of other users with whom they share a connection, and (3) view This subsequently widely adopted view stressed the centrality of social media users at the expense of the structural attributes of social media and the ways such attributes shape the premises of user platform participation that we point out in this paper.

ready. As Gillespie (2014) cogently remarked “algorithms are inert, meaningless machines, until paired with databases upon which to function. A sociological inquiry into an algorithm must always grapple with the databases to which it is wedded” (169). Algorithms do no operate in a vacuum. Without attention, we contend, to the operational details through which data are produced in standardized formats (Gillespie 2014; Kallinikos and Constantiou 2015), there is an obvious risk of reifying and mystifying algorithms, and their power to shape social relationships on the Web and beyond it (Couldry, Fotopoulou, and Dickens 2016). Our attempt to expose the infrastructural datawork by means of which social media platforms standardize and compute user participation is a response to the risk of reifying algorithms and misattributing causality. While we present our argument in significant conceptual and empirical detail in the sections following this introduction, it may be worthwhile rehearsing its basic components here to provide a larger purview of the article and its aims.

Social media operate by carefully organizing user platform participation along specific activity corridors (such as sharing, following, or tagging) that heavily stylize and shape user interaction. This engineering of user activity that we call *encoding* is a precondition for translating user interaction into suitable data formats that once recorded allow enlisting, enumeration, indexing and calculation of user platform participation (Alaimo 2014; Alaimo and Kallinikos 2016). The data produced by these means are then assembled or aggregated to form bigger entities. As we will see in the empirical part of this paper, new data entities are constantly established by the aggregation of tags performed by users on products in the context of social shopping platforms or, to refer to another context, by the aggregation of user likes on Facebook. *Aggregation*, thus, creates new data-entities out of the piling-up of singular, elementary platform activities encoded into data.

The data operations of encoding and aggregation are relevant because they explain how the data entities so assembled function as new social objects. By the term *social object*, we mean an entity[2] established against a background of expectations and practices that motivate and justify acting upon that entity (Desrosières 1998; Hacking 1983, 1986). In the case of social media platforms, individual users and collectives of users are new distinct social objects established against the rules and practices of data operations we describe. The claim that individual users are objects established by social media may feel unsettling. But in online environments, such as those represented by social media, there are no irreducible entities, in the sense of flesh-and-blood individuals (Abbott 2001). It is thus important to make clear that from the point of view of social media platforms, individual users are no more than the aggregation of the clicks they perform. For the backend data-processing machinery of social media, an object exists only insofar as it is amenable to computational definition and machine ‘sensing’. A user (as opposed to a real person) is essentially computed on the basis of discrete and countable activities that translated into a data set make that user an identifiable, knowable and actionable object (Abbott 2001; Desrosières, 1998; Foucault 1970).

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[2] There is an old and vexed controversy in social science as to whether aggregate entities are real or nominal (see Desrosières 1998). For the purpose of this paper, we assume that aggregate entities result from the piling up of abstracted qualities or attributes of real objects and may thus lack immediate reality refererence to such objects (Ekbia 2009).

The encoding of user activity and the techniques of aggregation open up a range of *computing* possibilities that cast platform participation into calculable terms. Social media establish a dynamic regime of quantified interaction between user data and user behavior, whereby data generated by users are processed and fed back to them variously shaping their behavior. Platform participation is constantly dissected and reconfigured by data-based user recommendations, through platform restructuring or, otherwise, through the involvement of third parties such as advertisers or data analytics companies with which social media platforms collaborate.

It is vital to recognize that this constant reshuffling of platform participation through personalized recommendations serves a purpose. Short of a real context or embedded social ties, social media platforms have no other means to define platform participation but through the quantitative derivation of user similarities. Although in the following we expose the encoding, aggregation, and computation in depth using a social shopping platform case, these operations can be identified across a broader social media spectrum. For instance, on social media for music discovery such as Spotify or Last.fm, user listening behavior is quantified into play counts (the counting of how many times users listen to a track). The aggregation of play counts constructs quantifiable users that are made commensurable to other users through the count of plays. By assembling together user activities *qua* data, social media can compute how similar two or more users are. Similarity and a few other scores (e.g. popularity and trending) are used in abundance by social media and construct what we here call a *computed sociality*. On social media, user interaction, user engagement and community building are defined and shaped by the measures produced by computing the data footprint of a continuously shifting user platform participation (Alaimo 2014; Alaimo and Kallinikos 2016). The social implications of these fundamental operations have largely remained outside the limelight. It is a major aim of this paper to cast light upon the nature of such artificial and quantitatively derived sociality and the ways it is produced and used by social media. It suffices here to say that the calculation of similarity and popularity scores constitute fundamental operations through which social media serve a range of stakeholders (e.g. platform owners, marketers, data analytics firms, partners) including, admittedly, the users themselves.

The rest of the paper is structured as follows. In the next section we provide an exposition of the logic through which platform participation is organized, recorded and measured. We focus in particular on the aforementioned operations of encoding, aggregation and computation which we analyze in some detail. We then move on to the empirical study of a social media shopping platform. We unravel the infrastructural datawork of social shopping and how the platform conceives and orchestrates user actions by enlisting, counting and correlating user data. We subsequently draw upon the findings of the case study to refine and further develop our ideas. We suggest that social media platforms are better seen as post-transactional spaces that compute and trade the expressive and communicative social fabric they engineer. In the concluding section, we summarize our argument and position the distinctive contribution of our paper within a broader social science context.

Encoding, aggregation, and computation: Towards a theoretical framework

As noted, social media organize user platform participation along standardized activity corridors such as sharing, tagging, liking or following. We refer to the outcome of such organization as encoding to convey the technological codification and stylization of social activities into particular clusters or classes – for instance, the encoding of approval, agreement or engagement into Facebook likes (Gerlitz and Helmond 2013). Encoding forms the basis for enlisting, recording and categorizing user activities. It is the principal medium through which what is commonly referred to as social data, as distinct from user-generated content (UGC), are streamed into media platforms.

User-generated content entails the creation and subsequent posting or uploading of content such as comments or larger text-based expositions, photos, and videos. User platform participation evolves, in fact, around user-generated content and the communicative exchanges this entails. It is important, however, to distinguish between the content, say, of the uploading or posting (what users generate as content) and the very act of uploading or posting that content (social data). The activities of posting, uploading, tagging and so forth are distinct from the content they convey. They have significant value of their own, as they are taken by the platform owners as indicators of the preferences and choices of users. In this respect, encoding is set apart from all other social media operations through which data are processed, clustered and aggregated, and value is created for platform owners and partners. Encoding is primary, fundamental. It provides the technical grid that orders platform participation into standardized activity types that, recorded as social data, become the raw material for all subsequent operations computed on the basis of this data (Alaimo and Kallinikos 2016).

The formalized actions that social media encode into social data differ from traditional online activities and the ways these are recorded and monitored by commercial websites. Cookies, beacons, and tracking devices record clicking, browsing or buying activities as transaction data (Couldry and Turow 2014; Elmer 2004; Turow 2012). Encoding does not record transactions, or simple online behavior (e.g. time spent on web pages or click through rates); it does not record prior facts, which it then places online, nor does it categorize existing social activities (we do not usually 'follow' friends offline). Rather, encoding creates the actions which users are invited to perform and records the performance of such actions into distinct data fields. In this regard, it establishes the terms of user platform participation and involvement through the structuring of the user interface.

Figure 1 schematically captures the logic of encoding on the basis of which online participation is structured. The activity types or corridors of platform participation (e.g. liking, following, tagging) represent a drastic reduction of the complexity and ambiguity of the patterns of everyday living and interaction. Such reduction is *sine qua non* for computing platform activity. It procures out of daily social interaction and user behavior data that are discrete, countable, pliable and, thus, possible to aggregate and compute in a variety of ways to serve the commercialization strategies of social media as business organizations.

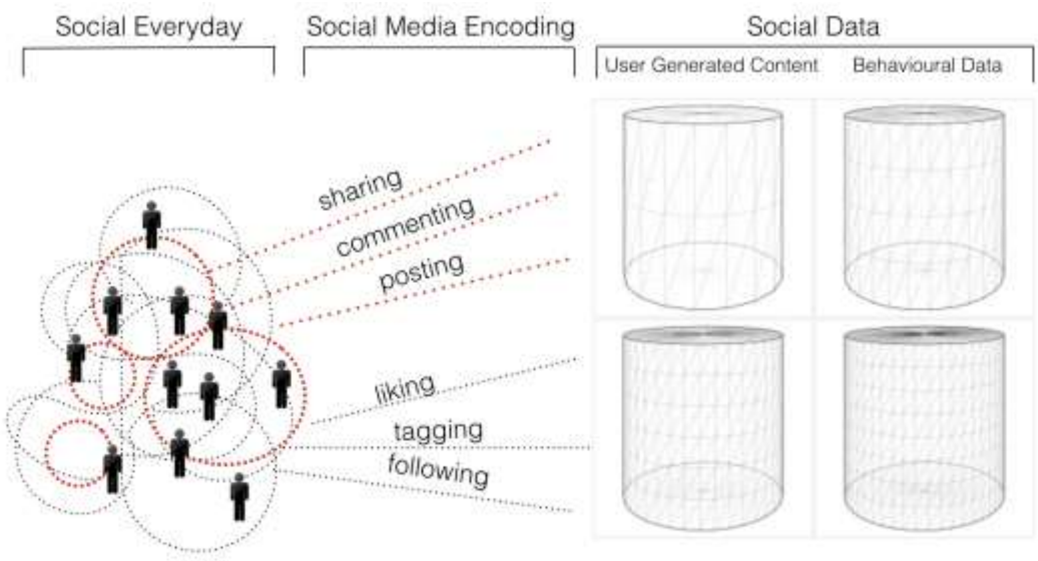

FIG. 1 — The encoding of platform participation by social media.

Viewed in this light, social media establish online a drastically simplified version of social interaction and communication. Essentially, on social media basic things or entities such as users, comments, photos, posts are all classified as data *objects* and every activity connecting two objects as *action*. For instance, Facebook defines status updates, pictures, videos, etc. as objects because in this way objects can be connected, or, as Facebook calls it, edged (Bucher 2012). Through this elementary syntax, every action undertaken on Facebook generates an edge, that is, a link connecting two objects. "Liking an object, tagging a photo, leaving a comment, these are all edge generators."[3] Encoding activities such as sharing, tagging, liking, and so on provide connections between two objects that can be further computed (see Figure 2). By processing the data resulting from the encoding of user interaction, the system is able to extract potentially meaningful sets of information on user behavior. For instance, in the case of Facebook, connections or edges are ranked under different criteria, such as how recent they are (what Facebook calls time decay), or how close the two end-users connected are (what Facebook calls affinity) (see Bucher 2012).

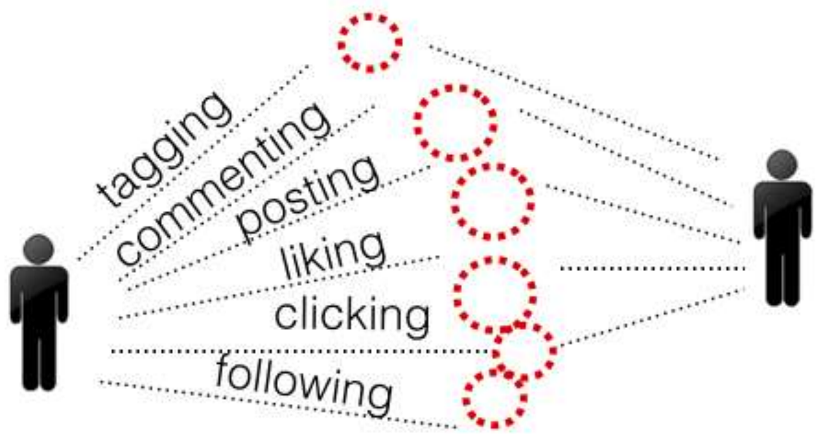

FIG. 2— The exemplified script of social interaction as encoding of data.

[3] See for instance Taylor (2011) "Everything you need to know about Facebook's EdgeRank" The Next Web (9 May 2011) http://thenextweb.com/socialmedia/2011/05/09/everything-you-need-to-know-about-facebooks-edgerank/ (Accessed on May, 3 2015).

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The figure shows the variety of actions as connections between objects.

A decisive step towards more elaborate computations is the piling-up of social data (the data resulting from the encoding of actions) into larger data aggregates. Piling up discrete individual activities into bigger entities helps establish the quantitative context of reference against which patterns of user actions become visible and relevant. For instance, on Facebook the success of a brand post may be defined by counting its number of likes that will become relevant only against the number of likes of other posts of similar or popular brands. As we will see in detail further below, the same logic of quantification established by aggregating a discrete activity into more inclusive entities holds true for the definition of any other object, users included. It is thanks to this formalized and standardized ways of aggregating data on user activity that social media can subsequently operate the personalization of content and other commercially oriented strategies such as targeted advertisement. Aggregation thus constitutes the second critical step in the infrastructural operations of social media platforms. It provides the means through which the scattered user actions encoded as data are pooled into larger data entities that form the springboard for further analysis and calculation that cast user platform participation in a different light.

It should be evident by now that by aggregation we do not mean the bringing together of diverse types of objects or services (e.g. news aggregates, brand aggregates, content aggregates), a common vernacular use of the term aggregation. Rather, we mostly deploy the term in its statistical sense to refer to the calculative operations that create a new, higher level, data entity out of properties or attributes of users as these last are defined by the platform encoding (Desrosières 1998). In this regard, aggregation is also an instance of abstraction that, although happening as backend system operation, helps establish out of the enlisted, singular actions of individual persons different or larger social objects such as individual users or collectives of users that are variously relevant to the functioning and objectives of the platform. Only when constituted as an aggregate of actions can each user or group of users be quantitatively associated to other users or to the entire network of users easily and efficiently. To go back to the well-known example of Facebook, defining an individual user as an aggregation of likes immediately renders the individual qua likes commensurable to other individuals qua likes. It is because users become comparable under the same unit of measurement (e.g. liking, tagging or following data) that social media can traverse the differences between individual users and describe platform activity by using various metrics such as similarity, popularity, or trending scores (Espeland and Stevens 1998). These scores, which for want of a better term we refer to as computation, recast user platform participation and sociality in terms of affinities derived from computing aggregated data.

In other words, the computability of aggregates makes possible scaling up and down the macro (network, community) -micro (user) ladder, under the quantitative groupings and categories established by similarity, popularity, or trending scores. With users construed as aggregates of actions, it becomes possible to compare and correlate them on the basis of a reference or unit of measurement (the like action, for instance). This unit constructs similarity (i.e., being similar with respect to the like action) and enables measurement against a context of relevance (a network or community of likes - where likes embeds particular assumptions). Thus, individual user actions, categorized and recorded as data (encoding) function as the raw material of quantitative grouping or classification (aggregation) that is drawn upon to construct a range of quantitative descriptions of platform activity (computation).

Figure 3 illustrates these fundamental steps and operations. The figure shows (1) the encoding of behavior into social data, (2) the aggregation of data and definition of new social objects as aggregate entities (users), (3) the computation of scores that subsumes diversity under the contingent categories established as measures, (4) the information output as personalized recommendations, and (5) user action. 'Real' individual users see just the last passage of these complex sets of operations, which by displaying personalized recommendations to act, comes full circle.

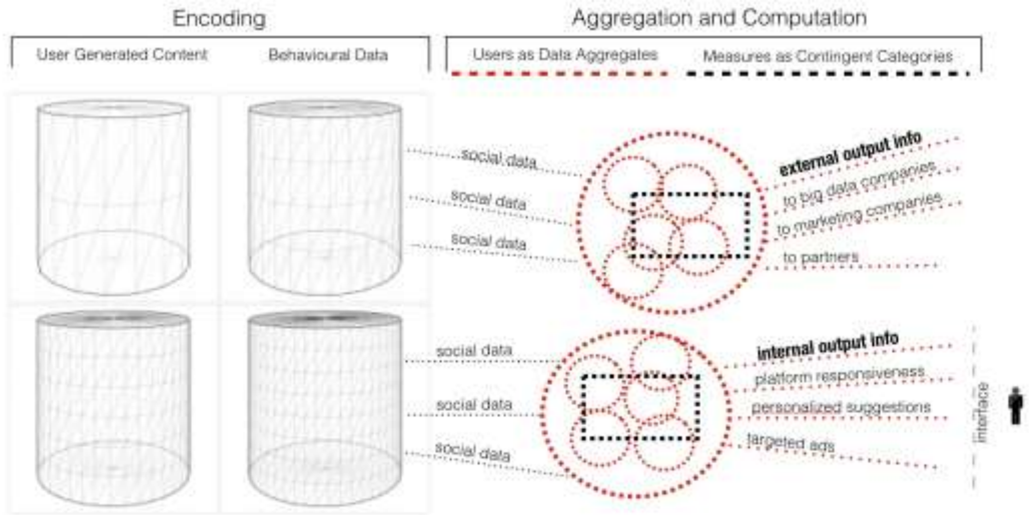

FIG. 3— The datawork of social media.

These processes are no doubt abstract and hard to grasp and assess. In the following, we draw on a case study that casts these operations in the context of a social media platform for shopping. While the platform provides a vivid example of the ideas just presented, our ultimate aim is to draw on the case study to refine and further develop our insights concerning the infrastructuring of social media and the complex systems of backend operations that define user experience at the front end. Before we embark on the details of the case, a few brief remarks on research design and methodology are in order.

Empirical setting: Research design and methodology

The social media platform we report on represents a *typical case* (Yin 2009; Flyvbjerg, 2006) of the shifting sociality context established by the processes of encoding, aggregation and computation already described. The platform provides an example of how the practices and significations characteristic of the social embedment of consumption such as imitation, class or group belongingness, fashion and taste exhibition (Lipovetsky, Porter, and Sennett 2002), are reframed and redefined to fit the online context of social media. This occurs through the encoding of user platform participation and the deployment of aggregation and computation to dissect and reassemble user online shopping behavior. In this regard, the platform is a specific instance of widely diffused technological systems and solutions that we have claimed are characteristic of the ways social media platforms operate (Alaimo 2014).

The case study has been conducted with the view to developing the theoretical framework already presented and further refining it through the identification of issues and relations not entailed in the original conceptualization (Flyvbjerg 2006; Yin 2009). We have collected information concerning the orchestration of user platform participation (encoding) and the data techniques the platform used for making sense and analyzing (aggregation and computation) individual and collective patterns of user activity. The key objective was to draw on the detailed, specific and contingent character of these empirical data to refine and further elaborate the theoretical ideas presented in the preceding section. For these reasons, other relevant issues were not investigated, even though we steadily kept an eye, for instance, on the ways the social media platform operated as business organization (e.g. business models and pricing strategies).

The empirical investigation was designed and conducted to unravel the *modus operandi* of social media from, as it were, the inside out. We assume that the ways social media platforms are structured and operate have a serious impact on what users can do on the user interface (see e.g., Kallinikos and Mariategui 2011; Marton and Mariategui 2015). Yet, such a focus should not be read as suggesting that social media as organizations exhaust user choices or the freedom users may have against systemic forces of technological, economic and organizational nature (see e.g., Faulkner and Runde 2012; 2013; Levy 2015; Zuboff 1988). All our stance assumes is that systemic forces of this type matter.

The case study fieldwork has been conducted over a period of 13 months in the company headquarters in London, UK (Yin 2009). Data were collected through ethnographic interviews of long duration (21), direct observations (23), demonstrations (5), company's internal (72) and external documents and reports (136). The fieldwork followed the procedures outlined by Yin (2009), adopting both a case study database and a case research protocol to maintain a chain of evidence. Data were analyzed by undertaking a first round of coding using thematic analysis (Boyatzis 1998), followed by the corpus construction technique (Bauer 2000). Corpus construction is a data analysis procedure that allows classifying unknown phenomena under known categories. Corpus construction was undertaken by building three subcorpora (known categories) derived from the theoretical framework (they are encoding, aggregation, and computation). Corpus construction is performed following a stepwise procedure: (i) to select relevant data, (ii) to analyze and increase the internal variety of the corpus data, (iii) to extend the corpus in order to reach saturation, that is the point where no additional variety can be detected (Flick 2009; Boyatzis 1998). The first case study narrative was checked and validated by one of the company founders (Yin 2009).

Piling up data: a social media platform for shopping

The social shopping platform has been described by its owners as a "Pinterest with shopping features"[4] that displays images of products that users can browse, searching for design products, design clothes and furniture. The platform relies mostly on social data and social media functionalities to transform shopping. It works very sim-

[4] Pinterest is a social media platform where users can upload, save and curate images (pins) in personal collections (named pinboards). The platform was founded in 2009 and by to 2015 hosted 30 billion pins, 70 million users and 40 million active members.

ilarly to a general social media platform: users can join using Facebook Authentication API[5]; they have their own profiles through which they curate and display their taste, they can follow other users with similar taste, or follow stores they like, and browse or search for products. The principle of the platform functioning is to let users save the products they like with a bookmarklet system[6] based on tags. User profiles are essentially constituted of images of products saved (tagged), other users, stores or brands followed, and of the different lists users can create to re-order (curate) their products. By letting users tag, the platform sustains user engagement and participation in accordance with the typical social media strategy. Tagging or social tagging is one of the main tools of Web 2.0 and a principal example of what we here refer to as encoding.

Social tagging leverages platform participation to overcome the increasing fragmentation of online commercial spaces. The platform is a socially curated "Internet department store," as its founders call it, where it is possible to browse and search for products independently of the individual websites of brands and retailers. By tagging images of products from all over the web, users provide the content for the platform's home page. At the same time, by tagging images of products users also ingest product-data (and product metadata) to the platform's backend systems. However, the activity of tagging also constitutes the principal source of user behavioral (social) data. Similar to general social media platform activities, tagging is an action linking two objects: user and product. By tagging products, users not only collectively ingest data on products on the platform, but they also actively signal their own product preferences. When users tag, they virtually attach to a product a tag with their own name. Tagging is the fundamental activity of the platform. By tagging users not only generate the main content of the platform (product images), but they also produce social data about themselves and their taste preferences.

The technology behind the tagging action is at the core of the platform functioning. As noted, tagging is implemented by bookmarklets, programs that embed different functionalities. For example, bookmarklet one-click functionality connects the store website of the product's image that users tag to the platform. When users save the product (by tagging its image) into their platform's profile, the link remains embedded, connecting the product to its original source. Bookmarklets also have data extraction functionalities. When users perform a tag, bookmarklets ingest product data and metadata (product attributes as color, price and so forth) into the platform's back-end systems.

One of the reasons behind the implementation of social media functionalities into commercially oriented online spaces is the awareness that consumption in different sectors is influenced by identity, class or group belongingness, and imitation, taste exhibition and other social factors (Barthes 1983; Bourdieu 1984; Lipovetsky, Porter, and Sennett 2002). Such aspects of consumption have not been adequately taken into account in traditional commercial online spaces. Hence, the flourishing of social media for shopping in sectors in which social participation is an essential component of the consumption process, such as fashion retailing, music, and movies.

[5] APIs (Application Programming Interfaces) regulate the exchange of data and functionalities between connected platforms or applications. An authentication API is used to join a new-connected platform using already existing user credentials.
[6] A boookmarklet is a JavaScript program, which adds one-click functions to a browser or web page.

The social media platform we present here seeks to encode this social aspect of consumption through tags and other social interactivities. The platform aspires to transform online shopping through personalized suggestions that, differently from traditional commercial spaces, derive from computing social data.[7] Because of this specific objective, the platform also differs from general social media in having a stronger sector-specific orientation. It is interested in learning a specific aspect of social participation: the influence of the social context on user intention to shop. The core assumption behind the social shopping platform is that by crunching social data it is possible to make more effective shopping suggestions, because social data capture the social aspect of consumption and therefore stay closer to user real needs and wants.

To summarize, the core platform activity of tagging procures the content, that is, images of products that are then reordered and displayed into the platform homepage. Tagging also procures data and metadata on products. Even more importantly, tagging constitutes the fuel that drives platform participation, making possible to encode the activities users perform into social shopping data for the platform's system. The one-click functionality embedded in tags sustains also the platform's business model, a traditional affiliate marketing model.[8] When users want to buy a product they simply click-through the image displayed by the platform landing onto the commercial website (store or retailer), which, upon the transaction being realized, pays a percentage to the social shopping platform.

The encoding of social shopping

The social shopping platform is based on data procured by the encoding of shopping and its social context. Similar to general social media, the platform encodes as data something that was invisible before: what the platform founders call *intention to buy* expressed by the core activity of tagging. Differently from general social media, the platform has an interest-specific orientation. It encodes the social side of shopping: the user intention to buy as this is expressed against the display of products tagged by other users (other users' intention to buy). The underlying assumption is that tagging and a set of additional actions, such as following, effectively encode the social side of shopping. The action of tagging is thus assumed to manifest user preferences. By tagging and thus saving product images into their own profiles, users express their own taste in computable forms.

These programmed set of actions formalize user participation as data that, so encoded, become the base upon which the system personalizes suggestions to buy through the construction of similarities to the activities of other users. In addition to tagging, users can follow other users or stores and eventually buy products. Aside from these two basic or explicit actions the platform's system also records a set of more implicit actions such as click on product images, browse products or search for specific products that are assumed to be related to user preferences and ultimately to their

[7] Traditional commercial spaces base their recommendation on transaction data (or clicks) and operate in the absence of a social context. On Amazon for instance users are suggested to buy on the basis of other similar customer purchases but they don't see what other users (or Facebook friends) are shopping or what they have in their wish lists.

[8] Simply defined, affiliate marketing is a performance-based marketing where a business (merchant) pays one or more affiliates on the basis of each visitor the affiliate is able to bring to the merchant.

intention to buy. By defining and structuring a set of different actions variously related to the intention to buy, the platform acquires the possibility of ranking the strength of the user intention to buy. The actions programmed are thus assumed to cover the spectrum of buying intentions, ranging from the more explicit intention to buy (tag) to other activities (e.g. search) that implicitly or indirectly relate to buying. In so doing, the platform further quantifies user intention data that can now be ranked from the most explicit (thus most valuable) to the less explicit (thus less valuable) (see Figure 4).

This translation of a previously informal social context of buying into discrete and stylized actions is a good illustration of how encoding streams into the platform the data on the basis of which a far-reaching computability of buying intentionality is made possible. It is for this reason that the platform's system takes tagging and not buying as the principal indicator of user taste preferences. The platform is predominantly oriented towards encoding user buying intentionality in the broader context of social shopping. The underlying motive is to transform shopping by uncovering new patterns, correlations or insights on user intention that precede buying actions and derive from social interaction data. In order to escape the formalisms characteristic of traditional marketing categories and segmentation techniques, the platform, according to its owners, adopts a social data bottom-up approach to buying behavior. "Data instead of content" (as the platform's slogan recites) will eventually personalize and transform buying. It means that suggestions to users are made not on the basis of editorial picks, style blogs (content) and other traditional ways of influencing buying decisions characteristic of the industry but just on data crunching.

FIG. 4—The explicit and implicit actions of social shopping encoded as intention to buy.
Each action performed by a user connects a user to a product and it is ranked from the most explicit manifestation of user's intention (tagging which is also called saving) to the most implicit (browsing). Each action is performed against the display of other users' intention to buy.

Users as aggregations of tags

As claimed earlier, on social media user participation is structured into standardized actions that are encoded as data-connections between objects. In the case we describe here, a link between two objects does not simply become countable as action data. The data-link carries also a set of assumptions that are functional to the computational operations the system performs. The tagging action connects a user-object to a product-object. It works as product-user relational data matrix. On the one hand, once a user tags a product, the product becomes charged with user intentionality. On the other hand, the user becomes charged with the product data and metadata (e.g. product type, price) as indicators of user intention to buy. The functional assumption of tagging is that the action qualifies products as coveted objects and users as potential consumers.

A further step in the computational rendering of consumption is the definition of users as aggregations of product tags. The platform's system constructs the user-object as piling-up of tags. As the engineer responsible for the design of the database explained:
"Users are defined by what they have been saving [tagging], in a way a user [object] is nothing more than a store [object]" (Interview).

The system creates two objects from the aggregation of tags: users and stores. The reason is clearly functional. By defining users as aggregations of tags the system makes them computable, comparable and amenable to inference and other quantitative modelling.

The rationale behind aggregation is to ground single, trivial and scattered events (tagging) or markers (tags) by making them appear as part of the same category of events. This is exactly the way tags work; they make sense insofar as they are considered as single occurrences of users' intention to buy, where a user is designed as an aggregation of tags. Tags allow the commensurability and computability of the user intention to buy. By having created objects of a superior level (i.e. users as consumers) through the aggregation of tags, the system renders commensurable users because it computes events that do not have value *per se* but only as markers of a cause of a more general level: the user intention to buy. Aggregation is scalable, always working the same way for every object. By piling up tags, it defines an individual user as well as a group of users. Because of this, the difference between one user and a group of users, or one user and the entire platform's user base, becomes just a matter of quantity of discrete data (tags).

Conceiving and defining the user-object as an aggregation of tags gives the system the possibility to compute following (the action linking two users *qua* objects) as a milder indication of the consumer intention to buy. As one of the engineers of the platform explains:
"The fact that you follow a person or you retag from a person is not as strong as the product tag, but is an indication of the taste you have as well*, so if you measure all the users that you are following as aggregated product objects* and you see that they are tagging mostly accessories, then this would be the indication that you like accessories, so it's almost the reverse engineering of the reason why you follow them" (Interview).

This is made possible just because users have been defined as aggregates of product tags (see Figure 5). Comparison between users becomes a matter of counting tags. Aggregation renders users commensurable by using tags as a unit of measurement. As the preceding quote explains, an indication of user intention to buy (his or her taste) may derive from the measurement of all the other users he or she is following, simply because they are aggregates of products. If they all like accessories, the system will assume that that particular user is interested in accessories.

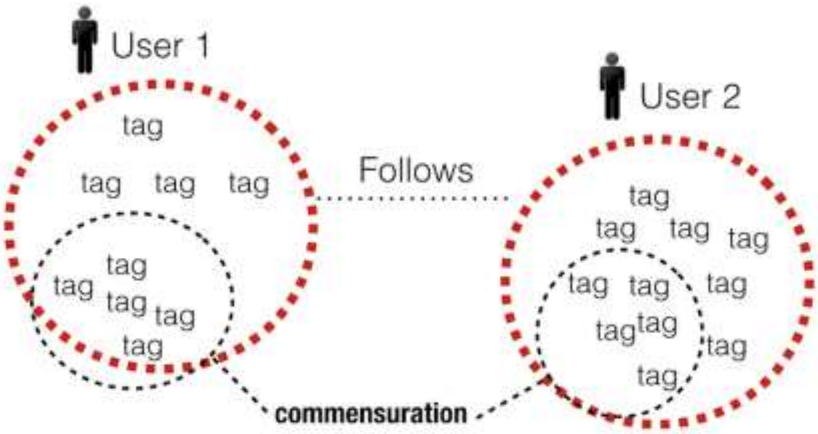

FIG. 5—The following action.
The figure illustrates how the following action between two users is rendered commensurable by defining users as aggregations of tags.

Computation of taste

The use of following action as less explicit indication of consumer intention to buy is justified by the fact that following, as tagging, is user generated. Actions on social media can be user generated, suggested or automated by the system or, as more often happens, be the combination of all these options. The specific implementation history of the following activity on the social shopping platform we studied clarifies the matter.

Originally, the platform automatically set a user's following. That is, when a new user joined the platform, the system automatically assigned to the newcomer some followed users. The automatic following were mostly the result of computation of Facebook likes. For instance, the system checked whether two users had liked the same brands or stores on Facebook or whether they had common friends. The automation was chosen as a partial solution to the so-called *cold start problem* that many social media platforms have in common. At the beginning of the activity the data sample is too low and is very difficult to achieve statistical relevance for personalized suggestions. Effectively, the problem lurks behind every newcomer. Every time a new user joins, he or she has no tags and no activity and the only way to suggest products becomes to associate him or her to a network of active users. In this respect, social data such as Facebook likes obtained when a newcomer joins the platform using the Facebook Authentication API fill the gap. The social shopping platform acquires user's likes, his list of friends, his friend's likes and some other demographic data which it uses to construct suggestions of following.

After the first automated following attribution, the platform received harsh criticisms from some of its users and decided to change the way following actions were implemented. It thus designed a step-by-step process whereby newcomers are asked to follow some users, brands and stores suggested on the basis of Facebook data. As noted, following is treated as a milder indication of user intentionality. By using following data the platform is able to compensate for the lack of tagging data of the newcomer by using tagging data from followed users.

Followed users form a network which is assumed to be of similar users. A user (newcomer) is thus assumed to share his or her taste within a network of similar users. Following data, even when resulting from a combination of user-generated and automated data, are at the basis of the similarity measure. Rather than being inferred by observing user buying intentionality or common attributes, online similarity is computed on the basis of following. When two or more users are connected by a following, they are automatically assumed to be similar in taste, and the computation of how many tags they share (a similarity score) is used to produce personalized suggestions.

Similarity together with popularity are the two measures that sustain the platform personalization system. Popularity, the measure regulating the display of products to users, can be personalized along different criteria. Popularity can be used to order the products of the entire platform's user base (all the products tagged by all the users). In this case the measure is called *trending*. Popularity can also be computed so as to order only the products tagged by an individual user networks (similarity networks). Popularity is obtained by computing how many times a tagged product has been retagged. Once a user tags a product, and the product image is displayed into his or her own profile and enters into the product feed of the platform, other users see it and can retag it. As one of the founders of the platform explains:
"The retag thing is really hard to cheat (…) so it's a good measure of the reality of something, or of the expertise on something" (Interview).

A tag that is retagged becomes popular – thus more visible – and as a consequence it has more possibilities of being retagged, changing not only the social landscape of the platform consumption but, literally, redefining users who tag and retag it. It is taken as a good measure of "the reality of something" (interview).

Measures such as popularity do not simply qualify products. Rather, given that users are defined as aggregations of tags, such scores constantly requalify users qua consumers as well. Popularity obtained by computing retags is taken as a good measure of the social approval of products and users alike. It does not simply attribute value (relevance) to objects as result of correlation and computation but it also creates economic value. As mentioned earlier, the platform is a for-profit company that relies on an affiliate marketing model. A popular product is a product that has more possibilities of being seen and thus bought. Furthermore, the company is also involved in the production of data analytics for marketers and retailers. Popular products make the popular consumers that the platform is able to signal as evangelists or influencers to retailers and marketers alike.[9]

Discussion: The infrastructuring of social media

In this section, we draw on the case study reported on the preceding pages to refine and further develop our ideas on the infrastructuring of social media and how encoding, aggregation and computation shape user interaction and platform participation.

[9] In marketing an evangelist is a type of loyal customer that actively and voluntarily becomes brand advocate or ambassador acting as marketer on behalf of the brand or the company.

We organize the discussion around three major emerging themes. The first theme reflects on the nature of social media platforms as designed social spaces in which task-based transactions (either in the form of buying or in the form of executing a routine) assume lesser significance as compared to the charting of the communicative and expressive life of users. An important consequence of this is the profiling of users and their tastes on the basis of their platform behavior (i.e., mostly what they express or say) as distinct from user purchase or transactional history. The second theme takes these ideas further by considering the key concept of computed sociality. We discuss how the design of platform experience provides the basis for the construction of a quantified and, ultimately, tradeable social everyday (Alaimo and Kallinikos 2016; Yoo 2010) in which users are steadily compared to the platform behavior of other users through the production of similarity and popularity scores. The third theme deals with how social media categorize user experience and sociality in ways that break with established practices of classification (Bowker and Star 1999; Douglas 1986; Weinberger 2007). To the new habits of living diffused by social media use corresponds a pervasive way of representing, measuring and categorizing sociality in terms of scores, derived from the perpetual datafication and updatability of a designed platform experience. Taken together the three themes attest to the relevance of our theoretical framework but they also refine and expand it in several ways.

Engineering experience: Social media platforms as post-transactional spaces

The case study presented in the preceding shows how user platform participation is designed in ways that respond to the data requirements of the platform and the business context within which it operates. Tagging and following constitute the key platform data-generating actions whereas clicking, searching, and browsing are less fundamental but still important actions that complement and variously qualify the data provided by tagging and following (see Figure 4).

Taken together, these elementary and standardized action scripts encode user participation in data formats that enable the quantification of user buying intentionality and its social context as well as its ranking along a continuum from less to more explicit. In line with the operations of other social media platforms, tagging is designed to be the spine of the platform we have studied, its core interaction (Choudary 2015; Parker, Val Alstyne and Choudary 2016), so to say, that generates the most valuable source of data. Tagging is assumed to be straightforwardly connected to buying, because it requires the active expression of user buying intentionality. Formalizing, quantifying, and ranking something as ephemeral and idiosyncratic as individual and collective buying intentionality is the real product of the shopping platform and its *raison d'être* as a social media-based business organization.

Such a state of affairs offers a striking and instructive contrast to digital retailing platforms (e.g. Amazon, Alibaba or eBay) for which buying, and the revenue it delivers, constitutes a core operation and key business objective. The contrast between actual buying and the charting of the intention to buy casts the understanding of social media platforms in an interesting light. Linking our case to our theoretical framework and a wider literature (Gerlitz and Helmond 2012; Helmond 2015; Van Djick 2013), we claim that social media platforms are spaces that have been set up to fashion predispositions, preferences, opinions or, as in our case, intentions out of an engineered platform experience. In most essential respects, social media as platforms are not set up to deal with transactions, other than as a by-product of their back-end data operations. Rather, social media are data platforms concerned with the production, technological infrastructuring and, ultimately, trading of user profiles or tastes derived from a designed sociality (Aaltonen and Tempini 2014; Alaimo and Kallinikos 2016). This is in our case being translated into the datification of the social side of shopping which, fundamentally, amounts to the quantitative transformation of conventional small talk associated with the prospect of buying, framed as social activity, and the deduction of individual buying intentionality from it. The distinction is largely applicable across social media platforms either of specific (e.g. TripAdvisor, Spotify) or generic (e.g. Facebook, Instagram, Pinterest) type.

None of these objectives can be accomplished without first engineering an artificial context in which standardized (encoded) user actions are aggregated at several levels (individual user, user groups or networks, and platform in its entirety) and then co-related by means of similarity and popularity scores. To achieve these goals, social media need very large volumes of data. This is where the design of easy and recursive actions such as tagging or liking acquires relevance. Particularly for the computation of personalized suggestions, any social media platform needs to reach very soon a good enough sample of data to support statistical inference (Jannach, Zanker, Felfernig, and Friedrich 2010; Konstan and Riedl 2012). Platform experience is thus engineered so as to procure these data by means other than buying transactions.

These ideas lead us to believe that the design and datafication of a social everyday are fundamentals means through which social media operate as post-transactional spaces. Social media platforms are predominantly concerned with the production, computation, and commercial relevance of platform data and only secondarily with the instrumentation and execution of user transactions. This is an important qualification of the original ideas presented at the frontend of this article. The two are, of course, related. In our case, the intention to buy cannot but be assessed by the reality purchase it carries and, ultimately, by whether it leads to buying. The same holds true for every user taste profile crafted out of the communicative and expressive fabric of an engineered platform experience. However, social media platforms disturb, loosen, or otherwise restructure the relationship between, on the one hand, predispositions, opinions and beliefs and, on the other hand, actions hardwired into real life contexts. They do so by hugely enlarging the space in which people as users are profiled by the typified ways of expressing and communicating on platforms rather than by real commitments (transactions) across platforms and other contexts of social life. Ordinary activities such as buying, reading news, or travelling acquire a secondary importance for social media as compared to engineered activities such as tagging, liking, commenting, reviewing, following.

On the other way around, digital retailers and commercial platforms (e.g. Amazon or eBay) increasingly incorporate user-generated data such as rating and reviewing into their operations and marketing strategies. It is hard to predict whether the difference separating social media platforms from other digital commercial spaces will persist in the future. Regardless, it is important to unravel the operative logic of social media platforms and the distinctive ways by means of which they engineer platform experience and trade its digital footprint. This leads us to the core issue of platform sociality we identified earlier in this paper (see, e.g. Helmond 2015; Gillespie 2010; Van Dijck 2013).

A computed sociality

The preceding observations suggest to us that social media platforms are social entities in an interesting and, perhaps, disturbing way. Social media are social insofar as they are concerned with the setting up and reproduction of a particular kind of sociality that is variously punctuated by the quantitative data operations they perform. How users are related to one another occurs against a platform context that is ceaselessly plowed and reordered by similarity and popularity scores. In our case, tagging defines users as potential consumers yet the results of tagging, namely products tagged, define the platform context in which users act: they are the display of the platform's community taste. Recall that all the platform actions with which users engage happen against the background of other user actions, a platform context whereby the individual display of taste happens as a socialized activity. Once again, this practice considerably differs from the way traditional commercial spaces operate. On Amazon, users are suggested to buy on the basis of similar users (similar transactions) assembled out of buying histories but they don't see what other users do. So, what kind of socialized context does the social shopping platform offer?

As seen, the platform is organized around the core activity of tagging and the data it procures. Tagging is not only instrumental to the goal of procuring social data. It also sustains the functioning of the platform because it operates as a unit of measurement. The tag, an abstracted marker of an assumed intention to buy, re-organizes data on the social and the social itself in a circular and recursive movement. The computation of tags constantly categorizes tagged products as well as platform users as potential consumers on the basis of the action of tagging. In this regard, tags qua data constitute the medium that sustains the definition of objects, as well as their position within a context and the context itself (the collective display of taste is stored as a data pool of tags). They indicate the relevance of information within a given context. By doing so, tags constantly reconstruct the very context they represent by means of the measures they help compute: differences, similarities, popularity and so on.

These observations take us to the cardinal issue of computed sociality and the types of 'communities' or 'networks' constructed by such measures as similarity and popularity scores. As we have seen throughout, similarity (similar users) and popularity (popular users or items) scores assemble together user preferences on the basis of data that the encoding of their actions (tagging, retagging, following) supplies. It is important to restate as clearly as possible that such user clusters are quantitative derivations of an engineered experience. They accordingly lack the social and cultural density (norms, social positions, values) of real communities or even other online communities underlain by the pursuit of a common objective or cause (such as open source communities or political networks) (Durkheim 2013; Douglas 1986; Shirky 2009).

Placed against this context, the framing of social media as traditional networks using social network theories or methodologies (Berger, Klier, Klier and Probst 2014; Whelan, Teigland, Vaast and Butler 2016) appears as a rather misplaced exercise. On social media platforms, users are not real persons but the aggregates of their discrete behavioral data produced by encoding. Our case demonstrates that user groups are not determined by real affinities of actors but by scores in a platform context that is recursively reordered by a shifting and continuously updated set of measures.

Even if social patterns on social media platforms may be visible as social networks, they are in fact shaped by the infrastructural operations we have analyzed in this paper (Kane, Alavi, Labianca and Borgatti 2014). This is why social media cannot be adequately analyzed at the level of the user interface and accounted for by the standard topological model of network analysis and its lack of structural depth (Emirbayer and Goodwin 1994; Knox, Savage and Harvey 2006). Rather, social analysis requires bringing to the fore the far-reaching importance of the backstage datawork that unravels the recursive relationship between user experience and the ways it is dissected, analyzed and used by social media. By the same token, much is glossed over when this complex fabric of heterogeneous data operations is equated with or, at any rate, subsumed under the notion of algorithmic determinations.

Our empirical study shows how similarity networks emerge and are conditioned by the infrastructuring work of data. For instance, networks of similar users emerge because of the recommendation of following. Following is recommended on the basis of a similarity score. In turn, the similarity score is established on the basis of following data. What we see is a recursive feedback loop between data and user behavior which becomes further reinforced by the social dimension of the platform. In fact, even if the platform social context is established by a set of scores and data objects, the user networks emerging from it eventually come to acquire social relevance (Levy 2015). It is true, for instance, that two users are deemed similar just because of their following data. However, platform users, as we have shown earlier on the case study description, see the products tagged by a network of similar users and to the degree they retag these products they come to reinforce the assumptions on the basis of which similarity is computed.

Contingent categories and the social context of classification

The social clusters or networks compiled by social media on the basis of similarity and popularity scores are no more than fake communities or pseudo-communities, a term that Beniger (1987) once appropriated from Robert Merton (1946)[10] to describe the historical move from personal to impersonal communication characteristic of mass media. If we are right, then social media platforms move beyond simply impersonating communication and social ties. They rather forge a context of social participation in which the ties of participants are, in most essential respects, data deductions and scores. Such context makes social media and the similarity and popularity scores they deploy very different from the quantified techniques and metrics for defining publics and audiences that have been ubiquitous in the media industry and its marketing clients since the second half of the twentieth century (Ettema and Whitney 1994; Napoli 2011).

The operations illustrated by the social media shopping platform presented above is a case in point. Such operations and their outcomes signal a rather dramatic difference with past practices of categorization and classification of consumers. Traditionally, individuals (as consumers) are the singular instances of a broader category of consumer or consumer type arrived at on the basis of demographic, income or life style attributes. By contrast, on social media, categories are continuously shifting

[10] Merton used the term pseudo-community to describe the fake bonds of affection between celebrated radio reporters and their audiences.

outputs of action data, whose value is expressed in quantitative terms. In our case, tags become the individual instances, the markers, on the basis of which new social objects are created and constantly recategorized. As we have shown in the preceding, on social media platforms, consumers are constructed as digital objects that become social once they act within a platform context. These new social objects are the result of data clustering and computation. They are defined as data objects with potential social relevance because of their computability rather than on the basis of what they are or to what category or social group they belong. Constantly shifting under the masses of data and the production of scores that such data enable, these new social objects have no stable identity or clear scope outside the expectations of computability of intentionality, or, more widely, the comparability of preferences or opinions. This allows for the infinite reuse and the portability of data objects across contexts that is so characteristic of the hyperconnected big data economy.

There is, of course, a long dispute in social theory and philosophy as regards the reality of aggregates and the social relevance of the measures one can extract from them such as averages, means or medians (Desrosières 1998; Foucault 1970; Svenonius 2000). Little wonder, there is no way to build categories without abstracting those attributes or aspects that justify the category, on practical or semantic grounds. But on the post-transactional context of social media platforms, the operations of encoding and aggregation and the computation of sociality scores carry categorization and cognitive grouping further into the realm of abstraction and artificiality. On the one hand, the engineering of platform participation establishes activity types with weak and often-obscure life anchorage that serve the purposes of aggregation and computation. What, really, is the purchase and true intentionality of actions like tagging and liking? On the other hand, due to the disengagement from socio-cultural contexts (Borgmann 1999), aggregation and the similarity and popularity scores computed out of aggregates establish countless possibilities of re-counting, recombining, and regrouping the data encoding procures.

In this context, categories are divested from their semantic and real life references and become opaque and transient data assemblies, just contingent measures that continuously adjust to new data actions and to their own regrouping. As indicated in our case, the contingent category of similarity (constantly shifting due to new following actions) is used to filter the popularity of products under personal pseudo-networks. That is, the platform tailors the suggestion of products to each user so as to reflect the characteristics of the similar others with which the user as an aggregation of data has been associated. We deploy the term *contingent categories* to refer to these ephemeral and steadily updatable cognitive clusters and underscore their contrast with the stability and social relevance of categories anchored in cultural, professional or scientific classifications and practices (Bourdieu 1984; Bowker and Star 1999; Desrosières 1998; Douglas 1986; Weinberger 2007).

Contingent categories are the outcomes of operations performed upon aggregated data. They are compiled out of the constantly updatable and configurable counting of user behavioral data, as engineered by social media platforms. Transforming online daily patterns of interaction into a perpetually refigurable data body is something that has never been done before. At the very least, it has not been done with the comprehensiveness, diligence and systematic mode of social media. In this respect, contingent categories mark a significant development that punctuates and maps platform behavior in dynamic, real-time-attuned ways on the basis of data that social media platforms engineer. Contingent categories diffuse across the social body the ceaselessly editable distinctions and computational outputs produced on the fly by a potent socio-technical apparatus.

Categorization is of course a complex, hugely subtle and contested issue (see e.g. Khalidi 2013; Lakoff 1987) that deserves its own lengthy treatise. Yet, the trend towards categories that serve no other than contingent purposes, seems to us to mark a new social and commercial practice that revives and, at the same time, transcends the standard issues and controversies of categorization and classification. The categorization contingent on platform participation classifies people and items together on the basis of transient user behaviors that hardly exist outside the engineered context of social media platforms. The temporal instability and rationalized nature of these practices and their ties to submerged data economies of user tracking and profiling constitute a fascinating and also scary subject that demands further investigation.

Concluding remarks

In this article, we have analyzed the infrastructural operations on the basis of which social media orchestrate user platform participation, and compute and trade its data footprint. Social media platforms frame social interaction in ways that reflect their own constitution as socio-technical entities. This implies that social media platforms purposely design various forms of user involvement and interaction as sources of social data with different value around which they organize their business activity. What we have called *encoding* translates user participation into suitable data formats that are subsequently aggregated and subjected to a series of calculative operations (similarity and popularity scores). *Aggregation* and *computation* cast platform activity in abstract yet socially relational terms, whereby each user and his or her actions are represented and quantified as data objects and always made sense of and assessed against the artificial context of other user's actions. Placed against this backdrop, our analysis has sought to unravel the grid of social and technological operations that on social media platforms render individuality and sociality measureable and convertible (Simmel and Frisby 2011) through the medium of what we call *computed sociality*. The term qualifies the concept of platform*ed* sociality (Helmond 2015; Van Dijck 2013) insofar as it connects user participation to the infrastructural layers of social media and delineates the role social media assume in shaping sociality.

The quantitatively produced relationality of user actions is the essence, we have claimed, of social media platforms and their *raison d'etre*. Social media platforms are social because of the very particular and historically distinctive mode of quantifying user actions in a platform environment that artificially reconstructs a certain everyday. It is relevant in this context to remind that much of user platform participation evolves around the communicative background of ordinary things (i.e. making friends, listening to music, buying, sharing photos and the like) that have traditionally been performed in various community or domestic contexts and have only marginally been infringed by market and institutional forces. An engineered version of this communicative background assumes now a primary role making social media platforms a particular type of digital platform (Choudary 2015; Parker, Van Alstyne and Choudary 2016; Sundararajan 2016). Social media are post-transactional spaces that focus on an artificially computed everyday crafted out of digital opinions, preferences, or intentions. Such data outputs acquire reality purchase and institutional relevance by being constantly fed back to the platform in the form of recommendations or by entering into various economic exchange circuits. Social data have now an important value and economic utility attributed to them by the growing ecosystem of platforms and markets in which social media are embedded (boyd and Crawford 2012; Helmond 2015; Proffitt, Ekbia, and McDowell 2015; Van Dijck 2013).

The backbone of the operations through which preferences, opinions and intentions are fashioned is the construction of users as *new social objects*. The novelty of the operations we have analyzed does not simply reside in their technical advances through which data are collected and managed nor in their underlying quantitative logic, their critical importance notwithstanding. Users as social objects should be viewed as institutional entities established against a background of expectations and practices that motivate and justify acting upon them (Desrosières 1998; Hacking 1983, 1986; Sismondo 1993). Social media platforms are able to construct users as aggregations of data and to trade the outcomes of their platform participation (more data) because they sustain and are sustained by a complex digital economy (Introna and Nissenbaum 2000).

No doubt, many questions lurk behind the claims we have put forth here. Some of them are of substantial nature and concern the social value or relevance of a computed sociality if, in all essential respects, the communities or networks it fashions are no more than data assemblages and computations pulled out of an artificial or designed everyday. The calculative operations of social media are based on data that have scarcely been available before the emergence and diffusion of the artificial forms of social interaction and user platform participation they establish. Such data are novel or, at any rate, differ from prior data, data classification systems and the institutional nuclei (e.g. state, corporations, mass media) in which such practices have been embedded (Napoli 2011; Porter 1995). It is thus important to study and understand the patterns and risks associated with a sociality produced on such artificial premises that render social media users and user networks convertible and amenable to a range of computational manipulations. Other remaining questions are of methodological nature and concern both the type of evidence we have drawn upon in this article, and the institutional variety of social media platforms. We need, no doubt, richer evidence on the backstage, infrastructural operations we have empirically investigated but also evidence that captures the diversity of social media platforms and accommodates or qualifies the claims we have put forward in this article.

Any analysis of social media, we suggest, that does not take into account their infrastructural operations and the institutional objectives they serve risks dwelling on the surface of a complex, tightly knitted and stratified sociotechnical and economic reality (Oestreicher-Singer and Zalmanson 2013; Sundararajan, Provost, Oestreicher-Singer and Aral 2013). The backstage, infrastructural operations we have described in this paper variously condition the terms of user participation and the emergence of frontend platform processes such as community building, user engagement, or network dynamics that may seem as the outcome of user deliberation (Kallinikos 2011; Kallinikos, Aaltonen, and Marton 2013). In analyzing these operations and showing their practical relevance in the context of a social media shopping platform, our paper makes a contribution to the mushrooming literature on social media, digital platforms, and to a social science interested in understanding the kind of socio-technical entities social media platforms are.

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