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Facilitating Organisational Fluidity with Computational Social Matching

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Abstract. Striving to operate in increasingly dynamic environments, organizations can be seen as fluid and communicative entities where traditional boundaries fade away and collaborations emerge ad hoc. To enhance fluidity, we conceptualize computational social matching as a research area investigating how to digitally support the development of mutually suitable compositions of collaborative ties in organisations. In practice, it refers to the use of data analytics and digital methods to identify features of individuals and the structures of existing social networks and to offer automated recommendations for matching actors. In this chapter, we outline an interdisciplinary theoretical space that provides perspectives on how interaction can be practically enhanced by computational social matching, both on the societal and organisational levels. We derive and describe three strategies for professional social matching: social exploration, network theory–based recommendations, and machine learning–based recommendations.

1 Introduction

Today, organisations operate in a dynamic environment in which organisational boundaries fade away, actors form new relationships spontaneously, and information flows in a chaotic way (Schreyögg & Sydow, 2010; Ståhle & Grönroos, 2000). Enhancing collaboration within and between organisations is considered a general recipe for improving their productivity and innovation capability (Hsiehchen, Espinoza, & Hsieh, 2015; Wuchty, Jones, & Uzzi, 2007). Particularly in knowledge work, collaboration is considered an effective means of dynamically solving problems and achieving exceptional results (Frydlinger, Nyden, & Vitasek, 2013). Following Schreyögg and Sydow (2010), among others, we conceptualise the more flexible organisational forms that result from these activities as organisational *fluidity*. One manifestation of fluidity is the emergence of more flexible and organic collaboration relationships.

In addition to fluid, we perceive organisations as communicative constitutions. In this vein, we follow recent scholarship in organisation studies arguing that communication is the fundamental constitutive force that brings organisations into being (Ashcraft, Kuhn, & Cooren, 2009; Putnam, Nicotera, & McPhee, 2009). Organisational fluidity refers to a way of operating in an increasingly complex environment by reducing the role of the boundaries, structures, and processes of the organisational container and, instead, operating through various partnerships, strategic alliances, and outsourcing networks with other organisations, crossing the boundaries of hierarchies, teams, and formal programmes (cf. Schreyögg & Sydow, 2010). Fluidity calls for new ways of managing and supporting the process of organising to make the most of increased collaboration while mitigating the problems that accompany increased complexity.

Social matching is an emerging research field that explores the identification and facilitation of new collaboration relationships 'in both physical and online spaces' (Terveen & McDonald, 2005). In knowledge work, social matching encompasses functionalities and decision-making related to, for example, networking, recruiting, partner identification, and team formation. Practical examples of social matching in this context include nudging individuals to meet each other (e.g., bringing together an entrepreneur and suitable business partners or advisors) and forming teams on the basis of complementary skills (Olsson, Huhtamäki, & Kärkkäinen, 2019). Social matching decisions vary from long-term and high-risk decisions (e.g., recruiting a new employee to an organisation) to short-term and low-risk decisions (e.g., introductions at networking events).

Computational social matching, accordingly, refers to the use of data analytics and digital methods to identify features of individuals or matching actors, to understand the structure of existing social networks, and to offer automated recommendations. We argue that by developing new computational solutions that utilise and refine data about knowledge workers, we can improve the understanding of individual and organisational features that impact mutual suitability. Related research has been carried out in fields such as person recommender systems (Chen, Geyer, Dugan, Muller, & Guy, 2009; Guy, 2015; Tsai & Brusilovsky, 2018) and decision support systems for human resources management (Gal, Jensen, & Stein, 2017).

In this chapter, we explore the use of computational social matching as a means of facilitating the emergence and evolution of the social connections within fluid organisations. Fluid organisations and their dynamic operating environment provide a fertile context for developing and conducting trials of computational social matching. In a fluid organisation, the organisational boundaries, structures, and processes fade away, and the actors consequently gain the freedom to form new social ties. Such fluidity is also present in cross-organisational settings, where active efforts are taken to facilitate the emergence of new organisations and organisational structures. Examples include cross-organisational collaboration relationships in business and innovation ecosystems (Russell, Huhtamäki, Still, Rubens, & Basole, 2015), adaptive spaces (Arena, Cross, Sims, & Uhl-Bien, 2017), and other forms of semiformal organisations (Biancani, McFarland, & Dahlander, 2014; Dobusch & Schoeneborn, 2015). Particularly flexible social structures are formed through the self-organisation between freelancers and piecework taking place on digital platforms (Alkhatib, Bernstein, & Levi, 2017). Authors such as Schreyögg and Sydow (2010) and Ståhle and Grönroos (2002) have maintained that such organising is a necessity for organisations working in the modern, dynamic organisational environment.

Computational social matching can be used to drive or support these efforts by facilitating the emergence of social connections within and between organisations, thereby supporting communication and the flow of information. We suggest that computational social matching can enhance the two main phenomena examined in the book, that is, society as an interaction space in general and service ecosystems in particular. First, computational social matching introduces core capabilities to facilitate new interorganisational collaborations that enable the emergence of society as an interaction space in a systemic way. Second, we subscribe to service dominant logic (Lusch & Nambisan, 2015), according to which service ecosystems are emergent actor-to-actor network structures where actors co-create value by developing and recombining services. Both the service ecosystem and its developers form an interconnected structure that can be computationally modelled and presented as networks and that reaches beyond the human capabilities in conventional social matching. Furthermore, the actors in a service ecosystem may include humans, services, and the technology that provides the means of communication.

This chapter takes a conceptual and theoretical approach to examining computational social matching in its role of facilitating the emergence and evolution of fluid organisations that are constituted through communication. Throughout this chapter, we use a fictional but concrete case of organisational partnership to illustrate our theoretical arguments. ACME is a media company that produces digital content both internally and in collaboration with freelancers. Bonk Ltd is an imaginary digital consultancy that co-creates value with its customer organisations by developing new digital services. Currently, ACME uses an information system to manage the production teams. Over time, ACME has accumulated data and information artefacts about the production teams, the skills, interests, and concrete tasks of team members, and the quality of production outputs. Bonk Ltd is experienced in developing services that support fluid means of organising.

Below, we first explain our theoretical premise—that is, organisations as fluid, communicative constitutions—connect that premise with the perspective of social networks, and then present the suggested strategies for computational social matching, using the ACME and Bonk Ltd case as an example.

2 Organisations as fluid, communicative constitutions

Recent developments in knowledge work have resulted in the need to rethink how organisations are defined and formed. Of the three types of organisational operating environments—mechanistic, organic, and dynamic—contemporary organisations operate in a dynamic environment, one that is global and forces them to collaborate and co-create value across their boundaries (Ståhle & Grönroos, 2000). This introduces changes into the structure and dynamics of interorganisational competition, and it forces organisations to adapt to various global and national political contexts and legislative and cultural environments. Organisations work, for example, in various partnerships, strategic alliances, and outsourcing networks with other organisations (Lee & Hassard, 1999). In the dynamic operating environment, the collaboration is so intense that the organisational boundaries fade away and the actors form spontaneous social ties that constitute a complex network in which information flows chaotically (Ståhle & Grönroos, 2000). Further, organisations are increasingly embedded in various digital service ecosystems (cf. Lusch & Nambisan, 2011), and they must therefore adopt digital practices of work and communication. To thrive, organisations must develop new ways of identifying the needs of their customers and stakeholders in a changing world and must co-create services and products to meet these needs.

Organisational fluidity has emerged as a theoretical and practical response to the 'increasing complexity and environmental turbulence that organisations have to master' (Schreyögg & Sydow, 2010, p. 1251). Whereas the classical view of organisations sees them as bureaucratically organised containers where humans and tasks are managed to produce output and social order (for a review, see, e.g., Reed, 2006), recent approaches define organisations as something more fluid and dynamic, such as networks (Borgatti & Foster, 2003; Lee & Hassard, 1999) or communicative constitutions (Cooren, Kuhn, Cornelissen, & Clark, 2011; Putnam et al., 2009). The network paradigm directs attention to the ways in which organisations come into being not as rationally managed entities, but as networks of people, that is, as social structures (Powell, 1990). Traditionally, organisations have been seen as sites where people are managed and their actions coordinated in order to achieve a common organisational goal (e.g., Ståhle & Grönroos, 2000), but a network perspective makes room for more dynamic views of the constitution of organisations and for an emphasis on interdependence. For example, in our example company ACME, the existing teams might be formed around identified tasks that take care of separate phases of the production process of a new media production. Alternatively, the teams could be formed on a more ad hoc basis, that is, as a changing network that emerges around each production separately, according to the needs of the production.

In line with the service-dominant logic (Lusch & Nambisan, 2015), the concept of mutual benefits is embedded in the view of organisations as networks; they are not designed as hierarchies but based on ongoing relationships, mutual reciprocity, and trust (Powell, 1990). This means that organisations are not bounded and that their memberships are not predefined; rather, they can form in an ad hoc manner via various collaborations that can also span traditional organisational boundaries. Hence, the ontology of interdependence and relationship is not limited to individuals in organisations but extends to networks, which can also form between organisational teams and even between organisations. However, as we explain in more detail in Section 3, hierarchical structures and repeated patterns are also found in networks. Such patterns of formal organisation are thought to make organisational structures more durable over time than networks (Porter & Powell, 2006).

It can be argued that in the current service ecosystem, the glue that forms the connections in a network is communication. The communication as constitutive of organisations (CCO) perspective is a theoretical account that advocates the role of communication in fluid organising. This account treats communication as the fundamental constitutive force that brings organisations into being (Ashcraft et al., 2009; Putnam et al., 2009). Instead of seeing organisations as preexisting entities, the CCO perspective posits that the organisation does not precede communication, but that it exists as communication and is formed in the various flows of communication among its members and other actors (Ashcraft et al., 2009). This makes organisations emergent, processual, and precarious entities that are constantly modified through communication. The CCO approach also acknowledges underlying network structures and the importance of nonhuman actors, such as technologies and documents, in the process of organising. According to Blaschke, Schoeneborn, and Seidl (2012), organisations are networks of communication episodes, unfolding over time in spatial and temporal settings. These networks take shape around symbolic or material elements (see also Taylor, Cooren, Giroux, & Robichaud, 1996). In the case of ACME and Bonk Ltd, the launch of a new production project could be considered an element that gives birth to new communication episodes as a given team of people begins to communicate about the project.

This chapter argues that if such communicative networks are allowed to form independently of organisational hierarchies and administrative structures, the organisation can develop more fluidity through the mutual connections between human and nonhuman actors. Organisational fluidity sets the actors free to form new social ties, which become social structures at the organisational and societal levels. Increasing and enriching human encounters not only adds to the actors' knowledge of the world and other people but enables learning and facilitates inspiration in a very natural way. From this ontological perspective, social matching technologies become a means of supporting the process of organising itself by ensuring that the right people communicate with each other. Instead of managerial team-building decisions, ACME could use a computational matching system to identify potential teams for each new production project and allow the teams to form in a self-organising manner.

It has been argued that the diversification of networks, partnerships, and collaboration brings about advantages at the individual, organisational, and societal levels in terms of exchanging knowledge and therefore improving creative and innovation capabilities (e.g., Mitchell & Nicholas, 2006). In certain situations, it would even be advantageous to first bring the actors together and allow the forms of collaboration and specific goals to emerge in interaction, following the principle of 'who before what' (Collins, 2001). Human actors, however, are prone to form social ties in a way that reduces diversity and limits the flow of information. Matching facilitates the emergence of communicative connections between actors in an organisation, and when it succeeds, it does so in a way that supports the organisation's goals, its identity, and its existence. In line with the words of Taylor (2009, p. 156), the product of this intercommunity coordination is the organisation itself.

3 Unfolding organisational social networks

Above, we resolved to consider organisations as fluid constellations, born in the network of communicative relationships between actors. In the context of social matching, we start from the premise that these networks form between nonhuman as well as human actors. Hence, as our subscription to the CCO perspective implies, we follow the main ideas of actor-network theory and relational sociology, which suggest that objects, such as laboratory tools or technological artefacts, become meaningful only in their interrelations and that various nonhuman entities play a role in these relational networks (e.g., Latour & Woolgar, 1979; Latour, 2005; You, Crowston, Saltz, & Hegde, 2019). In a social matching system, the nonhuman actors include the matching system and the information artefacts that are used to match people and build the network, commonly things like intangible skills, documents, or points of interest. Hence, this claim is in line with service-dominant logic and its view of service ecosystems as emergent actor-to-actor networks—with the addition, however, that we recognise the agency of nonhuman entities in such network systems.

The structure of social networks does not form and evolve randomly. Core regularities of networks include their scale-free nature (Barabási & Bonabeau, 2003) and small-world structure (Milgram, 1967; Watts, 1999). In social networks, 'scale-free' refers to the extremely uneven distribution of the number of connections among network actors. At the time of this writing, Katy Perry, Justin Bieber, and Barack Obama each have more than 100 million Twitter followers, whereas most Twitter users have only tens or hundreds of followers. Preferential attachment is the mechanism driving the emergence of scale-free networks. That is, the more connections the actors have, the more likely they will be to form new connections. The preferential attachment mechanism is sometimes referred to as the rich get richer or the Matthew effect. Such phenomena might also occur in smaller contexts; for example, in the case of ACME, it might be that the most senior employees with certain highly valued skills are the employees most frequently asked to join production teams.

The small-world structure is the hypothesis that all the people in the world are within six handshakes of each other (Milgram, 1967). The small-world structure is a combination of tightly interconnected communities of actors who are connected to each other through individuals who bridge the communities (Saxenian, 2006).

If we assume that fluid organisations are networks that are allowed to form independently, it is likely that they will also demonstrate the small-world phenomenon. A social structure that has evolved organically without constraints is composed of densely interconnected groups that are connected to each other through individuals who bridge structural holes. Following their intuition, a knowledge worker forms new social connections, most likely among their existing social circles, with similar individuals in close geographical or organisational proximity. Two mechanisms drive networking: homophily and triadic closure. The homophily bias posits that individuals seek company based on similarity (Kossinets & Watts, 2009; McPherson, Smith-Lovin, & Cook, 2001) and are therefore able to operate efficiently in the short term. At the same time, new connections are likely to be formed between pairs of actors who share a strong connection, that is, friends of friends (Granovetter, 1973). These effects have been shown to exist in organisational networks as well (e.g., Brass, Galaskiewicz, Greve, & Tsai, 2004; Hansen & Løvås, 2004).

When the aforementioned mechanisms are allowed to run free, the resulting social network structure likely unfolds as a mycelium of echo chambers or social bubbles. The echo chamber phenomenon involves the formation of densely interconnected groups of actors and the reduction of information within the groups. When a group is established, the group's opinions and information base will likely undergo increasing homogenisation. The phenomenon is amplified when group members who share worldviews continue to enforce each other's opinions. In extreme cases, echo chambers can be detrimental (Van Alstyne & Brynjolfsson, 2005). For example, in knowledge work seeking novelty, or when starting a new company or designing a service ecosystem, diversity is imperative (Aggarwal & Woolley, 2013), and heterogeneous, complementary knowledge is the driver of organisational success, and especially of innovation capability (Rodan & Galunic, 2004). Regarding ACME, would they build better and more innovative productions if the teams were more diverse?

Therefore, computational social matching needs to strike a balance between diversity and bandwidth of information exchange (Aral & Van Alstyne, 2011). On the one hand, it is important to support the formation of weak ties that serve as conduits of novel information between existing social groups, such as collaboration partners outside the organisation or the daily social circle. Social ties that bridge the structural holes in social networks enhance creativity and support the career development of the actors who form such connections, because their collaborators perceive them as sources of novel information (Burt, 2004). On the other hand, strong ties (Granovetter, 1973) enable the high-bandwidth exchange of information, because the actors forming these ties are likely to be similar to each other in terms of domain, knowledge, and shared vocabulary.

4 Facilitating organisational fluidity with computational social matching

Thus far, we have argued that fluid organisations let their actors operate with a greater degree of freedom than before. Moreover, we have described the mechanisms that come into play when individual actors network and collaborate, guided by limited information and their built-in biases. In this section, we describe how computational social matching can facilitate organisational fluidity.

In our view, a social matching system is a technology artefact that enables and facilitates such constitution by *suggesting and forming relationships of communication between the actors*. A social matching system is an information system artefact composed of technology artefacts, social artefacts, and information artefacts 'that together interact in order to form the IS artifact' (Lee, Thomas, & Baskerville, 2015). In this context, a machine learning–based software that runs the social matching service is a technology artefact, the new social ties that the system identifies and facilitates the formation of are social artefacts, and the 'instantiations of information' (Lee et al., 2015, p. 8), such as messages, articles, and documents of shared interest to the actors, are information artefacts. To facilitate social matching, a system should seek to identify combinations of human actors and information artefacts relevant to them.

When fluid organisations are examined through the CCO ontological lens, the interaction between actors is what forms and reproduces organisational structure. Developing algorithms that can facilitate the identification and formation of these interaction-based social connections is far from trivial. A fundamental challenge in the development of social matching systems is the need to accumulate high-quality data about the characteristics of knowledge workers, including their knowledge, skills, interests, and social networks (Olshannikova, Olsson, Huhtamäki, & Kärkkäinen, 2017). Also necessary is data about and models of the ideal forms, contexts, and objectives of collaboration and networking. The use of mobile devices, digital tools, and collaboration platforms implies that an increasing amount of data about knowledge work interactions has been accumulated (Bunce, Wright, & Scott, 2018). In the case of ACME, the prerequisites for a social matching system already exist, because the company has accumulated information about the skills and knowledge of their employees.

Schreyögg and Sydow (2010) pointed to monitoring and timely managerial interventions as means of managing a fluid organisation. Continuous, constantly evolving analysis and enacted sensemaking (Weick, Sutcliffe, & Obstfeld, 2005) allow individuals to operate independently of structures, support their agency, and transform the role of organisational leadership and management toward continuous development. Organisational monitoring can be considered a first step toward computational social matching when insights into the social structure are used to steer the actors in the organisation toward forming new connections. For example, upon the identification of a structural hole, the ACME organisation can seek to form new social connections, perhaps by refining production team compositions.

To counterbalance the biases in organic network formation and evolution, the default design principle in computational social matching is to increase diversity. There is no formula or even ideal for enabling organisational diversity that could be used to design a service that matches actors. Research has shown that gender, age, culture, and other surface-level differences diminish team performance, whereas attitudes, values, available information, and other deep-level differences enhance it (Mannix & Neale, 2005). Although social network structure is a known factor in performance, we do not know enough about the microlevel social interaction mechanisms needed in creative work to effectively utilise these mechanisms in social matching (cf. Holland, 2014).

To flesh out the foundation and scaffolding of computational social matching in fluid organisations that are constituted through communication, we now describe three complementary strategies for implementing social matching systems.

The first social matching strategy, *social exploration*, involves providing actors with interactive systems to support their identification of new social connections with suitable knowledge, competencies, and capabilities. A simple ordered list of actors that a user is able to sort by different features has proven to be an efficient approach in social matching (Tsai & Brusilovsky, 2018). Examples of measures that support the identification of potential actors include the distance between the actors in terms of social, knowledge, cognitive, and geographic perspectives. In ACME, this is a strategy that could be, to some extent, rather easily accomplished using the employee information already collected by the organisation.

The core design principle of this strategy is to present the data with a minimum amount of refinement. The benefits of such a simple system design include transparency and understandability. Taking a visual analytics approach supports transparency and enables enacted sensemaking (Bendoly, 2016), that is, continuous and flexible data exploration with the goal of identifying, creating, and sharing new knowledge about actors and the fluid organisation. Users are able to perform sensemaking and tailor the system to their changing needs and objectives. For example, it is possible to provide support for teasing out truly new ideas from a large social or geographical distance (Tsai & Brusilovsky, 2018), with the cost of reduced bandwidth. On the other hand, individuals that are socially and geographically close are able to serve on-demand information needs.

The second social matching strategy, *network theory–based recommendations*, consists of designing systems according to the theories and principles of social interaction and social network formation. When facilitating the communicative constitution of fluid organisations, the system must strike a balance between the diversity and homogeneity of the actors who are nudged to form new social ties. That is, the developers should follow the diversity–bandwidth trade-off (Aral & Van Alstyne, 2011) as the guiding design principle. As discussed in Section 3, introducing new weak ties is important when the social structure becomes static and the actors indicate that they are seeking new sources of information. Strong ties and more static structure is needed in times of convergence. As for the features other than social distance, balancing actor diversity and homogeneity is highly context dependent (Olsson et al., 2019). In this regard, both individual users and organisation management should be able to emphasise matching mechanisms that nudge individuals to form connections that may not seem relevant or intuitive yet could have long-term importance at the organisational or societal level. In ACME, such a strategy could mean that the social matching system would prefer forming connections that connect employees who have not worked together on production projects in order to maximise diversity and the formation of weak ties.

The third strategy for designing computational social matching systems, *machine learning–based recommendations*, rests on a data-driven approach and machine learning. Here, the guiding principle is to derive the social matching rules from data. Following the logic of supervised learning, two types of data are needed: first, data about actors and their interactions and, second, data that represents the actors and their interests, intentions, and subjective experiences during previous interactions. Supervised learning algorithms are trained using features representing actors and their social connections as inputs and the social matching objectives as outputs.

Following this strategy, Bonk Ltd could offer a computational solution to improve organisational fluidity at ACME by leveraging the existing data about employee skills and interests and by constructing a network of their past interactions and joint production using the historical data collected from the teams. The information about production output quality could be used to infer learning outcomes for the machine learning system, which means it would be defined by existing data about team performance. The performance of the matching rules derived with various combinations of features and algorithms would be compared until a satisfactory performance was achieved. When the algorithm was used in production, data representing the actors, interactions, and organisational social structure would be constantly refreshed.

Table 1 summarises and compares the social matching strategies from the viewpoint of the agency of different elements. The impact of a matching system depends on the data, technology choices, service developers' design choices, organisation management's interests, and the individuals' needs.

Table 1: Comparison of social matching strategies

Agency	**Social exploration**	**Network theory–based recommendations**	**Machine learning–based recommendations**
Individual	**High** An individual user can explore options and optimise the use for their own preferences	**Low** An individual may choose from given options, based on theory-derived reasoning	**Low** An individual may choose from given options provided by an opaque recommender algorithm
Management	**Medium** Management defines the general objectives and the rules of access to organisation-specific data	**Medium** Management defines the objectives and optimisation criteria	**Medium** Management defines data access rules, the objectives, and optimisation criteria
Developers	**Medium** Developers can choose which profile and network features are prioritised in the user interface	**High** Theories and their operationalisations selected by the service developers affect the matching logic	**High** Developers define the features, select machine learning models, and the training and validation procedures
Technology	**Low** Software frameworks define the rules and boundaries of visual representation	**Medium** Technology affects the formal models of actors and their social network	**High** Machine learning technology is available as modules with built-in rules
Data	**Low** Actors are able to perceive data categories and values	**Medium** Actor and social network representations are based on data	**High** Social matching rules are derived directly from data

Computational social matching systems rely on high-quality data about actor interactions and their impacts. The organisations must make sure to accumulate and curate such data to drive the matching logic and to support the knowledge of the teams developing such systems. We are the first to point out that data should not be treated as an objective input of the matching procedure. Both the data that an organisation has accumulated prior to the development of a social matching system and the data that is collected specifically for such a system are functions of the data collection systems. That is, the management and system developers have agency in defining how the data comes into being. At the present stage, it is likely that such data does not exist. Solving this issue by collecting subjective data about interactions is bound to change the way individuals act and observe the world. This is because awareness of being the target of observation and measurement changes the way humans behave (Leclercq-Vandelannoitte, 2017; Wickström & Bendix, 2000).

Moreover, developers and management define the boundaries and objectives for systems in all three strategies. That is, even systems that fall under the category of social exploration may, for example, nudge actors toward forming (or not forming) social ties according to what is perceived as favourable by the organisation. Nevertheless, allowing the actors to explore the data directly, such as with the help of appropriate visual analytics tools, improves the transparency of the system and the actors' awareness of organisational social structure.

5 Discussion

Computational social matching seeks to utilise data and algorithms to identify new potential social ties and facilitate their formation in organisations by selecting information and social artefacts of shared interest to the identified actors. In service ecosystems, human actors operate with each other, with services, and with other technological actors. The emerging network structure of such service ecosystems is an important driver of the activity; therefore, facilitating the evolution of the structure with social matching solutions plays an important role in avoiding the often detrimental effects of network mechanisms, including preferential attachment, homophily, and triadic closure. Treating organisations as fluid constitutions of communication further highlights the agency of not only human actors but the technology they use to communicate and to navigate the service ecosystems. Therefore, facilitating communication and interactions with technology has direct consequences for the structure and operation of organisations.

In this chapter, we presented three strategies for designing computational social matching systems: social exploration, network theory–based recommendations, and machine learning–based recommendations. In the first strategy, users are provided with interactive systems that afford a relatively objective means of exploring potential new collaboration partners and shared interests, potentially with a visual analytics approach to supporting actor-driven enacted sensemaking. However, these systems assume that the user is proactive. Moreover, it is likely that the degree of freedom enabled by such transparent systems will result in users following their natural, often suboptimal networking patterns. To overcome these problems, we suggested the use of a network theory–based recommendation system that builds on the mechanisms of social network formation to nudge actors to collaborate in a way that has long-term benefits at the organisational level. Such a system highlights the agency of the developers, who would be responsible for the operationalisation of the matching logic. In the third strategy, a machine learning–based system refines and learns from data collected from the actors and their organisations. This strategy gives developers a leading role in the formation of fluid organisations and therefore insists on transdisciplinary teamwork and close collaboration among the users.

In addition to the strategies for computational social matching presented in this chapter, a computational approach enables additional ways to support the transformation of emergent themes and self-organised groups into more established forms of organised activity, such as work groups, new commercial actors, or voluntary sector institutions. First, clustering the content of communication with, for example, unsupervised machine learning methods enables the identification of emergent themes of interest within broader established communities, such as discussion forums, large enterprises, or innovation ecosystems. Second, with social network analysis and the strategy of interactive sensemaking, one can identify relevant actors who are actively contributing to the substance or building the social capital around an emerging topic of interest. Third, semantic analysis of the communication may help unearth topics that represent relevant needs for new leadership endeavours or product development efforts in the existing organisations or that represent targets for the renewal and restructuring of organisational practices.

All three presented strategies rely on high-quality data about actor interactions and their impacts. While accumulating such data, it must be ensured that the data collection neither violates the rights of the individuals nor introduces unintended mechanisms as users become aware that they are being observed. Therefore, it is important to discuss and reflect on the ethical dimensions of building social matching systems. Do the expected advantages outweigh the potential risks? Are the advantages distributed evenly between individuals, across organisations, and between geographical areas? Building algorithmic systems like computational social matching applications is not a value-free activity, and researchers must be aware of the politics, ethics, and potential future consequences of such development.

First, the data required for computational social matching is personal—potentially sensitive—data and hence must be handled lawfully, fairly, and transparently, as required by the EU General Data Protection Regulation. Access to the data must be carefully controlled and the rights of the data subjects ensured. Who can view the data collected by the automated matching systems? How can individuals, for example employees at ACME, access their own data? What happens to the data after a person changes their employer or wants to opt out? Even more complex questions will arise if the social matching is done in an interorganisational setting.

Second, data analysis that involves profiling can be seen as suspicious or unethical, and the profiles generated can have profound consequences (Brayne, 2017). Several studies have discussed algorithmic bias (Caliskan, Bryson, & Narayanan, 2017; Zarsky, 2016) and the unintended adverse effects of computational systems (Friedman, Brok, Roth, & Thomas, 1996; O'Neil, 2016). For example, many current online recommendation systems in online stores favour popular objects for which data is readily available, leading to the Matthew effect discussed in Section 3. Essentially, these issues call for transparency of the algorithms (e.g., Kemper & Kolkman, 2018; Mittelstadt, Allo, Taddeo, Wachter, & Floridi, 2016) behind the matching. Systems based on machine learning, however, are typically unable to explain their recommendations to their users (Wachter, Mittelstadt, & Russell, 2018).

Therefore, it is of utmost importance to consider the goals and ideals potentially implemented in the social matching system—either explicitly, in designing the matching logic, or implicitly, by carefully selecting the training data (cf. Ruppert, Isin, & Bigo, 2017). Research in science and technology studies (e.g., Winner, 1980) has reminded us that all technology is embedded with implicit values and therefore has consequences beyond its immediate context of use. A social matching system needs some principles or standards that define its goals, and in a machine learning–based system, these principles will change over time as the system learns. Who defines the parameters for optimising the system, and who decides what is measured in the first place? How can the users evaluate the current reasoning behind the system?

6 Implications

Computational social matching systems can play an integral role in facilitating the emergence of fluid organisations that are constituted through communication. The success of their design depends on the practices of collecting, refining, and curating high-quality data about actors, their interactions, and the value of the outcomes of these interactions. Computational social matching systems can simply provide the data to the users, draw from the theory of social interaction and social network formation, or learn from past behaviour to recommend new combinations of actors. In all of these approaches, it is important to facilitate the formation of these collaborations by identifying relevant social or information artefacts of shared interest to the actors.

Social matching systems can and, as we argue, also should counterbalance the organic mechanisms driving social network formation and evolution. Densely interconnected social groups are a prerequisite for creating and aggregating knowledge efficiently and in way that facilitates innovation. It is equally important to form ties between social groups in order to establish conduits of novel information and break up echo chambers. Service ecosystems provide an exciting context for theoretical and practical experimentation on the agency of data, technology, and humans that continuously reorganise for ecosystemic value creation. We recommend starting the development from analytics and monitoring services with limited agency and moving gradually toward automatisation. It is imperative that such development ventures are inherently transdisciplinary and conducted in close collaboration with the users of the social matching system and other stakeholders by measuring and making sense of their response to the design.

If the collaboration between ACME and Bonk Ltd is successful, the envisioned social matching system can be generalised; that is, it can become a digital service that operates in a service ecosystem, drawing and analysing data from different organisations and weaving new social connections to facilitate society as an interaction space.

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