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Abstract: Knowledge work involves various so-called social matching decisions: who to recruit, who to pair up or team up, who to ask for consultancy, etc. Despite the scale of effects such decisions can have on organizations, social matching activities are little supported by technology. In this position paper, we describe an ongoing venture to develop the enablers and a shared vision for forming digital ecosystems around social matching of knowledge workers. Rather than developing monolithic, organization-specific systems, we argue for an API-based ecosystemic approach that helps co-create value and develop more networked, innovative, and viable business ventures. We elaborate our vision and work-in-progress by presenting requirements for and scenarios of digital ecosystems for social matching in knowledge work.

1 INTRODUCTION

This position paper stems from a research venture between two university research groups and a consortium of companies to develop the enablers and shared vision for forming digital ecosystems around social matching of knowledge workers.

What is social matching of knowledge workers? The general notion of *social matching* refers to computational ways of identifying and facilitating new social connections between people (Terveen and McDonald, 2005). Our focus is on social matching in professional life, particularly in creative and knowledge work. Relevant activities include recruitment of new personnel to knowledge-intensive organizations, team formation within or across organizations for various types and lengths of projects, seeking for mentors or advisers as an individual or an organization – basically, establishing any kind of collaboration relationships related to knowledge work. Today, social matching activities are labour-intensive and based on human judgment. Yet, the decisions have significant impact on the performance of organizations and the wellbeing of individuals (Rogers and Blenko, 2006). This makes professional matching decisions prone to human error, and the risk of making an unsuccessful choice is of high probability and high impact. We consider this as a fruitful opportunity to envision new forms of digital decision support systems.

What is an ecosystem, then? The key premise in business ecosystems is that in order to be competitive, companies must allow other companies to create additional value to their own offering. James F. Moore (1996) kicked off ecosystem discussion with his seminal article *Predators and Prey: A New Ecology of Competition* in which he states that companies should view themselves as part of a

> "... business ecosystem that crosses a variety of industries. In a business ecosystem, companies coevolve capabilities around a new innovation: they work cooperatively and competitively to support new products, satisfy customer needs, and eventually incorporate the next round of innovations."

In some 20 years, academic research has moved further to define several complementing types of ecosystems, including knowledge, innovation, and business ecosystems (Valkokari, 2015). In knowledge ecosystems, companies and research organizations come together to create new knowledge in pre-competitive phase of research and development (Järvi et al., 2018). Innovation ecosystems are interconnected, interdependent compositions of startups, founders, investors, enterprises, universities, public organizations that together drive the emergence of new companies, products, and services (Russell et al., 2011). Business ecosystems are composed of interdependent companies co-creating value to their cus-

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tomers (Iansiti and Levien, 2004). Although the use of ecosystem as concept in business and strategy literature remains a controversial topic (Oh et al., 2016), scholars are actively investigating this form of collaborative value creation (Ritala and Almpanopoulou, 2017; Russell and Smorodinskaya, 2018).

What makes an ecosystem digital? Digital assets are increasingly important in enabling and facilitating the emergence and success of ecosystems. API ecosystems are a recent example of enabling co-creation between companies through digital interfaces that help exchange data and simple services (Evans and Basole, 2016). Although Application Programming Interface (API) is a core concept in modular software development, in this context it refers specifically to Web APIs, that is, application programming that are available online for developers to use. Web APIs have existed since the early days of the World Wide Web and they had a core role for example in the Web 2.0 vision (O'Reilly, 2007). However, only recently technical and business developers have joined to explore this place of digital value creation they both find themselves in (cf., Evans and Basole, 2016). Digital ecosystem researcher Rahul Basole recaps:

> "Businesses must both own and participate in ecosystems. APIs make that happen. #digital #ecosystem"[1]

Our research venture has two key objectives. First, we seek to develop data-driven, interactive service concepts for professional social matching and related methodology. Second, we aim to explore ways to implement some of these service concepts at ecosystem level, that is, in co-creation between companies rather than within the corporate firewall. This paper describes our work-in-progress analysis of what type of ecosystems could be feasible from technology perspective and desirable from the perspectives of organization studies and social psychology, particularly in the relatively understudied area of social matching in knowledge work. We argue for the opportunities ecosystem thinking can bring in creating new digital services that facilitate professional collaboration. Ecosystem building starts from shared vision (Järvi et al., 2018; Russell et al., 2011) and our shared vision for ecosystem thinking starts with the API ecosystem approach. That is, instead of designing a monolithic platform-based ecosystem, our objective is to identify potential API-based collaborations on social matching, either among project consortium members or between consortium members and third parties.

[1]https://twitter.com/basole/status/1001477372460371969

2 NEED FOR DIGITAL SUPPORT IN SOCIAL MATCHING

Why the social matching activities in knowledge work require digital support? Choosing potential matches are traditionally manual tasks performed by busy managers or Human Resource professionals (e.g., matching an employer with a suitable employee). However, it is well known that decision-making is inherently limited by the human capacity of information processing—based on intuition, heuristics, and cognitive shortcuts (Kahneman and Tversky, 1973), and striving for minimizing cognitive effort (Fiske and Taylor, 1991). Human decision-making can result in tendencies like homophily, the preference of interacting with like-minded others (McPherson et al., 2001), and leaning on existing social networks and a geographically limited pool of candidates. For example, forming working groups in organizations often display arbitrary and ill-justified choices even though the combination of people can significantly influence the productivity of the group. This calls for digital support that can help considering options beyond the obvious (cf., Gal et al., 2017) and identify unexpected, yet meaningful social ties between actors.

Why should we care about ecosystems in the context of professional social matching? People are inherently interconnected with various other individuals and organizations, also outside their professional role. This means that the consideration of certain social ties should not limit to a particular matching activity; for example, a "good match" for a new headhunted recruit could turn into a relevant mentor or mentee in another context. Similarly, the needs for enhanced collaboration do not limit to one's primary professional role but relate also to secondary and tertiary roles, not to mention collaboration in the third sector, hobbies, and others.

Importantly, if we take a textbook approach to implement computational social matching, we end up developing a people recommender system that seeks to maximize there relevance of the recommendation. Actor similarity, the number of shared existing connections, and triadic formation of new connections are the key predictors of a connection. Therefore, the introduction of social recommender will only boost the formation of the traditional connections. On the other hand, knowledge work is fueled by complementary information, viewpoints and skills; this calls for systems that help increase epistemic diversity and unexpected social ties in and between organizations.

3 STARTING POINTS FOR SOCIAL MATCHING ECOSYSTEMS

3.1 Social Matching Analytics

Our approach to social matching is computational and data-driven. Specifically, we explore the use of Big Social Data (BSD) in identifying potential connections between actors. Olshannikova et al. (2017) define BSD as

> "any high-volume, high-velocity, high-variety and/or highly semantic data that is generated from technology-mediated social interactions and actions in digital realm, and which can be collected and analyzed to model social interactions and behavior."

Three types of BSD is available on individual actors. First, data on digital relationships that represent actors' social network. Second, transactional data on the interactions between actors. Third, actor-produced content, including their self-representations and discussions.

Social matching starts from the creation of network representation of the existing social connections between actors. Various data processing methods are used to extract features that represent the knowledge, competences, and interests of individual actors in algorithms. Once the network is composed and actors have their representation in algorithms, several alternative analytical option are available. Many of these approaches are based on pairwise analytics of the actors, including measuring their social distance and the similarity of their interests or produced content (Tsai and Brusilovsky, 2018).

Importantly, relevance-first approach is not advised in social matching analytics. Instead, social matching should seek ways to nudge actors to diversity-seeking behavior. Thaler and Sunstein (2008) define nudging as means to "alter people's behavior in a predictable way without forbidding any options or significantly changing their economic incentives." Means to implement nudging effects in social matching systems include the transparency, controllability, and explainability (Tintarev and Masthoff, 2015; Tsai and Brusilovsky, 2018). At the same time, we want to note that in general, social matching is an act of optimizing for the diversity-bandwidth trade-off (Aral and Van Alstyne, 2011). That is, both strong ties with high bandwidth and weak ties as sources of potential novel information are valuable to users.

3.2 API-based vs. Platform-based Ecosystems

Two basic architectures exist for digital ecosystems, that is, platform-based and API-based. In the platform-based approach, a keystone company operates a platform and provides the other companies means to develop complementary products. Apps built on mobile platforms is a prime example of a complementary product. On the other hand, API ecosystems are composed of dyadic service combinations. In API ecosystems, companies co-create value by providing Web APIs to each others consumption.

APIs are an important example of boundary resources. Formally, boundary resources are "the software tools and regulations that serve as the interface for the arm's length relationship between the platform owner and the application developer" (Ghazawneh and Henfridsson, 2013). Compared to platform-based ecosystems, API ecosystems are nimble and flexible. New combinations are easy to form and remove. API ecosystems are loosely connected compared to platform-based ecosystems. Twitter, for example, provides an API for developers to access data, including tweets and user profiles. Moreover, IBM Watson can be used through APIs.

Two basic types of APIs exist, data APIs and functional APIs. Data APIs have dominated in the early years of API development. However, functional APIs present an approach that does not insist a company to release their data to other actors but instead create value by implementing their own data products.

In our venture, the quest to develop ecosystemic social matching functionalities and services starts from an API-based approach. This is because we do not have a clear candidate to serve in the role of keystone that operates a platform. From technical viewpoint, social matching comes with a versatile set of use cases on collecting, cleaning, refining, modeling, and analyzing data. Due to this versatility, it is in practice impossible to implement a one-size fits all technical solution.

In order to manage the technical diversity, we take a component-based approach (Nykänen et al., 2007) to implement data-processing pipelines for social matching. This approach is an intuitive extension of our previous work on data-driven visual analytics that manifests as the Ostinato Process Model (Huhtamäki et al., 2015).

From a technical viewpoint, it is relatively straightforward to assign individual components to be run as services that different companies provision to each other. That is, reaching technical modularity is achievable simply by following API design principles. However, potential issues related to organizational modularity truly hinder the design of ecosystems. Once companies enter an ecosystemic collaboration, by definition they become interdependent to each other both at technical and organizational level (Ghazawneh and Henfridsson, 2011; Yoo et al., 2010). Data is a core asset to companies and therefore they are understandably reluctant to share the data to others.

3.3 Legal Constraints

The newly launched General Data Protection Regulation (GDPR) is truly a gamebreaker in Professional Social Matching. From BSD mining viewpoint, GDPR adds major restrictions. Data on individual actors can only be collected for a dedicated purpose and with informed consent. Moreover, acts of data-driven profiling must be reported to the actors that the data and resulting profiles describe.

It seems that platform-based services such as LinkedIn and Duunitori have an advantage in the GDPR age. These platforms are able to collect informed consent from users to a) profile them and b) make automated decisions (e.g., position recommendations for candidates and candidate recommendations for companies). Using harvested data does not seem to be an option at all.

4 SCENARIOS OF API-ENABLED MATCHING ECOSYSTEMS FOR KNOWLEDGE WORK

To make the intersection of social matching, knowledge work, and ecosystems more tangible, the following presents two scenarios of desirable futures. These shed light on our empirical work in progress and highlight the potential ecosystemic benefits and different types of API provider and customer roles in different realms of knowledge work.

4.1 Global Innovation Platform

A global innovation platform operates by taking problem statements (case projects) from companies and combining university student teams to work on the tasks for an intensive period of problem based learning. The innovation platform has staff to facilitate the projects, and each project team is able to exchange views with university-based topic expert. The projects produce different benefits for different stakeholders: important experience and connections for students, new learning platforms for universities, fresh ideas for the companies, and atmosphere of open innovation to the local community. This is an opportune ground for ecosystemic social matching scenarios. But how to identify which students form an effective team together? How to identify appropriate expert advisers for each project? How to identify which possible project topics are most suitable for this kind of innovation projects?

Data-driven team formation refers to a data-driven approach to compose and structure teams for new projects (cf., Zhou et al., 2018). Services for managing the workforce of an organization (here, a pool of available students) would provide a workable starting point for this scenario. With the growing trend to create digital portfolios and professional profiles online, these data about students could be analyzed for team formation, along with the data the university has about them. While these data can be privacy sensitive and indeed have multiple origins, the innovation platform would need an access only to an API that provides a list of key qualities that each student has or would like to learn. Ideally, the qualities would include not only skill and knowledge areas but also information about their general cognitive styles and suitable roles in team-based innovation work.

Second, universities are increasingly using Current Research Information Systems (CRIS) to help maintain researcher portfolios and gather data about academic output, such as publications, talks, awards and intellectual property. This portfolio data – intended to be public anyway – could be sourced to identify key interests and competences for each researcher and teacher in order to create features representing them in a matchmaking algorithm. These features would be matched with the project descriptions and the student groups. This insists that the university provides an API to the CRIS data. Interestingly, such API provision is well in line with open science and open access ideals but in stark contrast with GDPR.

Third, the innovation platform can accumulate data about past successful innovation projects and their characteristics. Using for example machine learning, we might identify what types of organizations, which project topics or what kind of customer involvement have yielded best results for the customer organization, for the student group, or for the society as a whole. This insight can be used to headhunt for suitable project from the local businesses and to select the most suitable teams for each case. As such data does not yet exist, it is crucial to define suitable measurements and practices of gathering relevant data systematically about each project.

4.2 Matching as a Service for Leadership

Matching as a Service (MaaS) is envisioned as a new initiative to provide an organization and its employees with digital support for various internal social matching cases. Particularly leadership and managerial activities, such as individuals' career development assistance, activity partnering for task forces and leisurely activities, finding a mentor, and ad hoc team formation for various short-term projects would be fruitful cases that are currently missing proper digital support. At the same time, in knowledge-intensive organizations and professions, people possess latent, untapped potential and tacit knowledge: many epistemic problems could be solved with the help of peers rather than by utilizing the conventional chain of command through the hierarchy. But how to efficiently identify what latent skills and knowledge different people have and who might need them?

The vision comes with an online platform that the employees use to state needs and requirements for leadership services, of which many fall under social matching. In order for this scenario to become ecosystemic, platform developer must provide boundary resources to allow third-party development of complementary services to the platform. The ecosystemic perspective could mean, for example, offering the identified skills or knowledge outside the organization to customers and partners. Partnering organizations could offer API-enabled leadership services to each other, especially in smaller companies without an established HR department. Alternatively, ecosystemic thinking could be advocated in smaller scale within the organization: giving more room for grass-root initiatives and for example internal startups. Particularly in large enterprises the organizational rigidity and silos call for enhanced interplay between actors in different parts of the organization.

5 CONCLUDING REMARKS

In this position paper, we described our vision of the building blocks of digital social matching ecosystems for knowledge work. We argued for the need for social matching within and in-between organizations and point to Web APIs, a key category of boundary resources, as digital means to implement ecosystemic co-creation relationships between organizations. We hope the vision encourages further transdisciplinary investigation of the practicality and real-life desirability of digital social matching in general and the ecosystemic approach in particular.

The current shift in legislation toward increased privacy and right to be forgotten and therefore limited data access (GDPR), as well as increased user control and machine readability (MyData) must be considered when planning ecosystemic digital social matching concepts. Need for informed consent from each individual separately seems to effectively prevent mining big social data *en masse*. That is, the existence of a social supercollider (Watts, 2013) for social matching seems unlike at this stage. This implies that global platforms for digital work posses a major advantage in developing analytical capability for social matching.

Future research should look into what are suitable and ethically sustainable design goals for social matching particularly in knowledge work; what kind of business models best serve API-based ecosystems in this domain; and how to enable gathering and analyzing relevant data in the current legislative landscape. Ecosystemic service concepts for social matching that cross the boundaries of individual organizations are yet to be developed. We will continue our venture to develop some of these concepts. We call for the exchange of viewpoints on privacy-opportunity tradeoff for ecosystemic digital social matching.

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REFERENCES

Aral, S. and Van Alstyne, M. (2011). The Diversity-Bandwidth Trade-off. *American Journal of Sociology*, 117(1):90–171.

Evans, P. C. and Basole, R. C. (2016). Revealing the API Ecosystem and Enterprise Strategy via Visual Analytics. *Communications of the ACM*, 59(2):26–28.

Fiske, S. T. and Taylor, S. E. (1991). *Social cognition*. McGraw-Hill, New York, 2nd edition.

Gal, U., Jensen, T. B., and Stein, M.-K. (2017). People Analytics in the Age of Big Data: An Agenda for IS Research. In *Thirty Eighth International Conference on Information Systems, South Korea 2017 1*, page 11.

Ghazawneh, A. and Henfridsson, O. (2011). Micro-Strategizing in Platform Ecosystems: A Multiple Case Study. In *ICIS 2011 Proceedings*.

Ghazawneh, A. and Henfridsson, O. (2013). Balancing platform control and external contribution in third-party development: the boundary resources model. *Information Systems Journal*, 23(2):173–192.

Huhtamäki, J., Russell, M. G., Rubens, N., and Still, K. (2015). Ostinato: The Exploration-Automation Cycle of User-Centric, Process-Automated Data-Driven Visual Network Analytics. In Matei, S. A., Russell, M. G., and Bertino, E., editors, *Transparency in Social Media: Tools, Methods and Algorithms for Mediating Online Interactions*, Computational Social Sciences, pages 197–222. Springer International Publishing Switzerland.

Iansiti, M. and Levien, R. (2004). Strategy as Ecology. *Harvard Business Review*, 82(3):68–81.

Järvi, K., Almpanopoulou, A., and Ritala, P. (2018). Organization of knowledge ecosystems: Prefigurative and partial forms. *Research Policy*, 47(8):1523–1537.

Kahneman, D. and Tversky, A. (1973). On the psychology of prediction. *Psychological Review*, 80(4):237–251.

McPherson, M., Smith-Lovin, L., and Cook, J. M. (2001). Birds of a Feather: Homophily in Social Networks. *Annual Review of Sociology*, 27(1):415–444.

Moore, J. F. (1996). *The death of competition: leadership and strategy in the age of business ecosystems*. HarperBusiness, New York, NY.

Nykänen, O., Mannio, M., Huhtamäki, J., and Salonen, J. (2007). A socio-technical framework for visualising an open knowledge space. In *Proceedings of the International IADIS WWW/Internet 2007 Conference*, pages 137–144, Vila Real, Portugal. Proceedings of the International IADIS WWW/Internet Conference.

Oh, D.-S., Phillips, F., Park, S., and Lee, E. (2016). Innovation ecosystems: A critical examination. *Technovation*, 54:1–6.

Olshannikova, E., Olsson, T., Huhtamäki, J., and Kärkkäinen, H. (2017). Conceptualizing Big Social Data. *Journal of Big Data*, 4(1):3.

O'Reilly, T. (2007). What is Web 2.0: Design patterns and business models for the next generation of software. *Communications & strategies*, (65):17–37.

Ritala, P. and Almpanopoulou, A. (2017). In defense of 'eco' in innovation ecosystem. *Technovation*, 60-61:39–42.

Rogers, P. and Blenko, M. W. (2006). Who Has the D?: How Clear Decision Roles Enhance Organizational Performance. *Harvard Business Review*.

Russell, M. G. and Smorodinskaya, N. V. (2018). Leveraging complexity for ecosystemic innovation. *Technological Forecasting and Social Change*.

Russell, M. G., Still, K., Huhtamäki, J., Yu, C., and Rubens, N. (2011). Transforming Innovation Ecosystems through Shared Vision and Network Orchestration. In *Proceedings of Triple Helix IX International Conference: "Silicon Valley: Global Model or Unique Anomaly?", July 2011, Stanford, California, USA*, page 17, Stanford, California, USA.

Terveen, L. and McDonald, D. W. (2005). Social Matching: A Framework and Research Agenda. *ACM Transactions on Computer-Human Interaction*, 12(3):401–434.

Thaler, R. H. and Sunstein, C. R. (2008). *Nudge: improving decisions about health, wealth, and happiness*. Yale University Press.

Tintarev, N. and Masthoff, J. (2015). Explaining Recommendations: Design and Evaluation. In *Recommender Systems Handbook*, pages 353–382. Springer US, Boston, MA.

Tsai, C.-H. and Brusilovsky, P. (2018). Beyond the Ranked List: User-Driven Exploration and Diversification of Social Recommendation. In *Proceedings of the 2018 Conference on Human Information Interaction&Retrieval - IUI '18*, pages 239–250.

Valkokari, K. (2015). Business, Innovation, and Knowledge Ecosystems: How They Differ and How to Survive and Thrive within Them. *Technology Innovation Management Review*, 5(8):17–24.

Watts, D. J. (2013). Computational Social Science: Exciting Progress and Future Directions. *The Bridge*, 43(4):5–10.

Yoo, Y., Henfridsson, O., and Lyytinen, K. (2010). The New Organizing Logic of Digital Innovation: An Agenda for Information Systems Research. *Information Systems Research*, 21(4):724–735.

Zhou, S., Valentine, M., and Bernstein, M. S. (2018). In Search of the Dream Team: Temporally Constrained Multi-Armed Bandits for Identifying Effective Team Structures. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems - CHI '18*, pages 1–13.