Scaling Mentoring Support with Distributed Artificial Intelligence

Ralf Klamma[1][0000−0002−2296−3401], Peter de Lange[1][0000−0002−3494−7513], Alexander Tobias Neumann[1][0000−0002−9210−5226], Benedikt Hensen[1][0000−0001−5421−4029], Milos Kravcik[2][0000−0003−1224−1250], Xia Wang[2][0000−0003−0849−5645] and Jakub Kuzilek[2][0000−0002−8656−0599]

[1] RWTH Aachen University, Aachen, Germany
{lastname}@dbis.rwth-aachen.de
[2] DFKI, Berlin, Germany
{firstname.lastname}@dfki.de

Abstract. Mentoring is the activity when an experienced person (the mentor) supports a less knowledgeable person (the mentee), in order to achieve the learning goal. In a perfect world, the mentor would be always available when the mentee needs it. However, in the real world higher education institutions work with limited resources. For this, we need to carefully design socio-technical infrastructures for scaling mentoring processes with the help of distributed artificial intelligence. Our approach allows universities to quickly set up a necessary data processing environment to support both mentors and mentees. The presented framework is based on open source standards and technologies. This will help leveraging the approach, despite the organizational and pedagogical challenges. The deployed infrastructure is already used by several universities.

Keywords: Mentoring Support· Learning Analytics · Cloud Computing · Distributed Architectures · Infrastructuring · Intelligent Mentoring Bots

1 Introduction

Mentoring is the process of the mentor supporting the mentee, in order to make the learning experience more effective and efficient. Psychological and emotional support are at the heart of the mentoring relationship, underpinned by empathy and trust [15]. In modern higher education institutes, mentoring has become challenging due to the mass of students and the lack of resources. It has raised the interest in socio-technical support for mentoring processes, which include peer mentoring and technological processes.

Intelligent Tutoring Systems (ITS) have a long tradition, focusing on cognitive aspects of learning in a selected domain. They were successfully applied especially in those areas, where domain knowledge can be well formalized with the help of experts. However, motivations, emotions and meta-cognitive competences play a crucial role in education. They can be monitored through big educational data and a wide spectrum of available sensors, bearing the potential to also improve the mentoring process. In this paper, we look at these various aspects and investigate how they can be technologically supported, in order to specify the requirements for Intelligent Mentoring Systems (IMS). This helps us answer the following questions:

1. How can we design IMSs to cover typical challenges and to scale up mentoring support in universities?
2. How can we design an infrastructure to exchange data between universities in a private and secure way to scale up on the inter-university level?
3. How can we integrate heterogeneous data sources to facilitate services supporting mentoring processes?

With our contributions, we aim at providing an Open Source Software (OSS) infrastructure and ecosystem for mentoring support from distributed Artificial Intelligence (AI). In the remainder of this paper, we first explore roles in the mentoring process and present our learner model that builds the basis for our approach to scale mentoring support (Sec. 2). We then present related work (Sec. 3), before we describe our scalable mentoring support infrastructure, based on a socio-technical approach (Sec. 4) and conclude our paper (Sec. 5).

2 The Pedagogy of Mentoring

Mentoring can be viewed from both the side of the mentor and mentee. The latter needs prompt and effective assistance, which means that the interventions should be not only without long delays, but also personalized to the individual needs and context. On the other side, the mentor is often overwhelmed with too many questions and requests of various complexity. Some of them can be automated. Others might be successfully answered by peers. The third group requires the unique competences of a mentor. Thus, the challenge is to properly categorize the requests of mentees and delegate them to an appropriate respondent: machine, peer or mentor. From such a solution, both sides can benefit. The mentee gets the required support faster and the mentor can concentrate on those requests that really require her expertise.

Considering this, we propose knowledge services for the automation of the mentoring process, based on the traditional models of *domain*, *pedagogy* and *learner*. The domain models are represented by RDF graphs, which can be manually created or extracted by tools, like for example T-MITOCAR [13]. The pedagogical models are based on rules, which will be enhanced with machine learning approaches at a later stage of our research. Our learner model is designed to serve the following purposes:

1. Assessing the learner's performance and knowledge level by using learning results to estimate her competence. A mathematical model combining Item Response Theory (IRT) and Transferable Belief Model (TBM) can be used for computing competence [4].

2. Dynamically and adaptively providing learning content, based on the learner's current knowledge competence and coverage. Only the unlearned, misunderstood and most related knowledge material will be suggested for further learning.
3. Evaluating the learners's learning process against personal goals. The learning is periodically evaluated and intelligent assistance will be provided if the learner is found to be behind or away from her goal.
4. Providing real-time interactive feedback to learner activity and recommending more related assignments and learning resources.

3 Related Work

ITS [1, 3] have already a rather long tradition in university teaching, and their role as virtual mentors in mentoring processes has lately been recognized [5]. Topics like peer mentoring, virtual mentors, affective and emotional support [16], but also minorities [9] and modeling [2] have been discussed. Mentoring can provide multiple roles [15]: counseling, instruction, training, activation, motivation, socio-emotional support, networking and example. There are also other success factors that make mentoring effective, like similar values, demographic proximity, trust and respect. Many of them have been already considered in existing approaches, including affect detection, meta-cognitive support, lifelong mentoring or prediction [7].

The role of a mentor can be taken over by a chatbot, a software program conducting auditory or textual conversations. Natural Language Understanding (NLU) can be applied to analyze speech, and intelligent responses can be created by designing an engine to provide appropriate human-like responses. The results of a systematic literature review [17] show that chatbots have only recently been introduced in education, but they offer opportunities to create individual learning experiences. This can lead to an increase in learning outcomes and can support lecturers, as well as their teaching staff [11]. Chatbots have also been extended in the field of mixed reality, which describes a spectrum between the real world and a purely computer generated world with the intermediate forms of augmented reality and augmented virtuality [10].

Measures of infrastructuring [12] allow to deploy fast software development processes that provide high quality tools for mentors, to set up intelligent virtual agents for supporting the mentees' needs. A modular approach, driven by containerized microservices, simplifies the setup of massively distributed systems. Such systems fall in the area of Infrastructure as a Service (IaaS), which are characterized by the provision of an infrastructure in which applications can be developed and set up.

The Learning Record Store (LRS) is a server responsible for receiving, storing and accessing learning activities. It can be operated as a stand-alone system, but it can also be integrated into a Learning Management System (LMS). In the latter case the LMS takes over the reporting and analysis using the data of the LRS, while the LRS connects to other activity providers. It also provides the possibility to connect to another LRS for further analysis of data from other sources. A LRS builds the basis for an Experience API (xAPI)[3] ecosystem, an OSS specification of a data format for learning data. Any interaction from a tool via the xAPI is done through the LRS, allowing the system to store and retrieve xAPI statements. Those statements contain information about the actor, verb, and object. When an actor interacts with the tracked system, the verb describes the type of activity and the object describes what is being interacted with. In addition to these predefined data fields of the xAPI, several extensions are available to allow a highly customizable storage.

4 A Distributed Architecture to Scale Up Mentoring

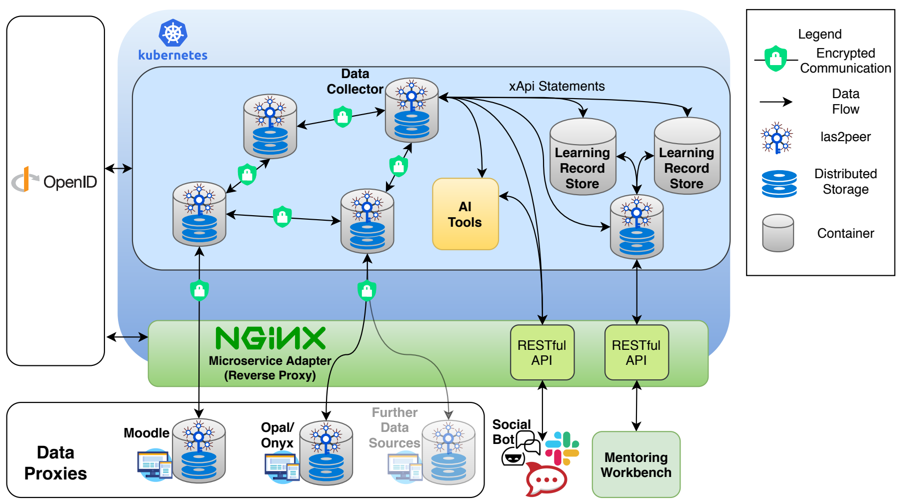

Fig. 1. Mentoring support infrastructure.

Fig. 1 gives an overview of our current infrastructure. Applications are installed and operated within a kubernetes cluster. The storage of the data is done decentrally by las2peer [6], a decentralized, OSS environment for community-oriented microservice development, deployment and monitoring. las2peer respects the demands of users for privacy, security and informational self-determination. The las2peer architecture consists of nodes connected by an underlying peer-to-peer network without central authority and hosts several services that can communicate with each other. The decentralized data storage and the communication within the network is protected by asymmetric encryption. This means that the control of the stored data remains with the respective stakeholder group

[3] https://xapi.com

(community). A Blockchain-based service registry [8] allows secure archiving of services with different versions, which in turn makes it easier to find and access them. Our infrastructure is connected to the learning toolchain via so-called *Data Proxies* for different LMSs, which are located at the institutions of the respective testbed. The task of them is to transfer the data from the respective LMS to the cluster. Currently, this is integrated for the LMSs Moodle and Opal. The incoming data flow from the data proxies is aggregated within the cluster via a monitoring pipeline and streams into a collection of connected LRS. This data is currently analyzed by basic knowledge services, which provide traditional models of domain, learner and pedagogy, based on both rule-based and machine learning approaches. In the future, smart assistance services will use this data to implement a spectrum of supporting functionalities, including personalized recommendations, categorizations, predictions and reflections.

As interface for both mentors and mentees, we use Intelligent Mentoring Bots (IMBots), chatbots tailored especially for mentoring processes. They integrate into common messaging platforms and provide just-in-time feedback. These IMBots are trained with the OSS RASA NLU[4]. Additionally, a *Mentoring Workbench* integrates back into the respective LMS, providing the mentees with both the possibility to use the IMBot from within their known environment, as well as giving them feedback on their performance. We use an OpenID Connect (OIDC) server to access all services in a modern and secure fashion. By coupling the OIDC identity and end-to-end encryption, the need for a central instance through which the communication takes place is eliminated.

5 Conclusions and Outlook

We have a proven technological platform based on international standards, existing OSS tools and a track record of EU-funded projects. The cluster has been set up as a public infrastructure and every external entity is able to connect to it. Data is currently coming from several German universities within a project funded by the German Federal Ministry of Education and Research (BMBF) and from a Massive Open Online Course (MOOC) supported by an ERASMUS+ project in the field of augmented reality. Our strong socio-technical conceptual framework allows us to develop our infrastructure, which supports both mentor and mentee in various organizations, following different legislative and organizational procedures, different LMSs as well as diverse target groups. Our development process, based on OSS commitment, allows us to quickly react on changing user requirements and organizational restrictions. In particular, end user involvement is supported from the beginning by the public formulation and elicitation of requirements in the Web-based *Requirements Bazaar* platform [14]. Given the early status of the data processing, with first example data sets that have been successfully evaluated, we will report on them at a later point.

[4] https://rasa.com

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References

1. Brusilovsky, P., Peylo, C.: Adaptive and Intelligent Web-based Educational Systems. Int. J. of AI in Education **13**, 159–172 (2003)
2. Dimitrova, V., Brna, P.: From Interactive Open Learner Modelling to Intelligent Mentoring: STyLE-OLM and Beyond. Int. J. of AI in Education **26**(1), 332–349 (2016)
3. Dugénie, P., Jonquet, C., Cerri, S.A.: The Principle of Immanence in GRID - Multiagent Integrated Systems. In: OTM Conf. pp. 98–107. Springer (2008)
4. Faulhaber, A., Melis, E.: An Efficient Student Model Based on Student Performance and Metadata. In: Proc. of ECAI 2008, pp. 276–280. Frontiers in Artificial Intelligence and Applications, IOS Press (2008)
5. Hoffman, R.R., Ward, P.: Mentoring: A Leverage Point for Intelligent Systems? IEEE Intelligent Sys. **30**(5), 78–84 (2015)
6. Klamma, R., Renzel, D., de Lange, P., Janßen, H.: las2peer – A Primer. In: ResearchGate. ACIS Working Group Series (AWGS) (2016)
7. Kravčík, M., Schmid, K., Igel, C.: Towards Requirements for Intelligent Mentoring Systems. In: ABIS '19. pp. 19–21. ACM Press (2019)
8. de Lange, P., Janson, T., Klamma, R.: Decentralized Service Registry and Discovery in P2P Networks Using Blockchain Technology. In: Web Engineering. LNCS, Springer (2019)
9. Mack, N., Cummings, R., Huff, E., Gosha, K., Gilbert, J.: Exploring the Needs and Preferences of Underrepresented Minority Students for an Intelligent Virtual Mentoring System. In: HCI Int. 2019, vol. 1088, pp. 213–221. Springer (2019)
10. Milgram, P., Kishino, F.: A Taxonomy of Mixed Reality Visual Displays. IEICE Trans. on Inf. Sys. **E77-D**(E77-D No. 12), 1321–1329 (1994)
11. Neumann, A.T., de Lange, P., Klamma, R.: Collaborative Creation and Training of Social Bots in Learning Communities. In: IEEE CIC 2019. IEEE (2019)
12. Pipek, V., Wulf, V.: Infrastructuring: Towards an Integrated Perspective on the Design and Use of Information Technology. J. of the Assn. for Inf. Sys. **10**(5), 447–473 (2009)
13. Pirnay-Dummer, P., Ifenthaler, D.: Automated Knowledge Visualization and Assessment. In: Computer-Based Diagnostics and Systematic Analysis of Knowledge, vol. 1, pp. 77–115. Springer (2010)
14. Renzel, D., Behrendt, M., Klamma, R., Jarke, M.: Requirements Bazaar: Social Requirements Engineering for Community-Driven Innovation. In: RE 2013. pp. 326–327. IEEE (2013)
15. Risquez, A., Sanchez-Garcia, M.: The Jury is still out: Psychoemotional Support in Peer e-Mentoring for Transition to University. The Internet and Higher Education **15**(3), 213–221 (2012)
16. Toala, R., Gonçalves, F., Durães, D., Novais, P.: Adaptive and Intelligent Mentoring to Increase User Attentiveness in Learning Activities. In: IBERAMIA 2018, pp. 145–155. LNAI, Springer (2018)
17. Winkler, R., Söllner, M.: Unleashing the Potential of Chatbots in Education: A State-Of-The-Art Analysis. In: Academy of Management (2018)