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A Concept for Productivity Tracking based on Collaborative Interactive Learning Techniques

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***Abstract*—The academic success of individual students differs widely and it depends on various factors, ranging from financial to social and to health aspects. In this article, we propose a concept for a novel productivity tracking system that provides the basis for a self-assessment of academic behaviour and that can be used by students to support their academic success. The development of such a system requires interdisciplinary efforts, most of them located in the field of collaborative interactive learning (CIL) that is grounded on a socio-technical system perspective. The system is interactive since it is based on bi-directional communication, collaborative in the sense that it uses students, other students, and external sources such as the Internet for generation of knowledge, and learning in the sense that it continuously and autonomously acquires knowledge. It is further self-organised as it decides about interaction partners and self-adaptive in terms of modifying its behaviour according to changing conditions.**

I. Introduction

The primary goal of universities is the education of students. In general, it is the responsibility of each student to self-organise his/her studies and to gain the best possible result. However, we observe that the academic success of students differs widely, which is only to a certain degree caused by methods and approaches of the individual university. Consequently, the question arises why some students obviously perform better than others.

There are some externally measurable factors that have impact on the students' success: Do they have to work for financing their studies? Or do they suffer due to (permanent) illnesses? These and further aspects such as stress, mood, workload, sociability, sleep, and mental wellbeing have a large impact on students academic performance [1]. The idea of this article is to develop a system that supports students by self-assessing their own academic behaviour in order to rate their productivity.

Technically, we propose a smartphone APP that is connected to a centralised cloud component. However, the main functionality is based on self-adaptive and self-organising behaviour since the individual instance of the APP is autonomously customising the internal models and relies on self-organised interactions with the user and other distributed systems. In order to assess the productivity of the user as well as his/her mental or behavioural state, an interdisciplinary approach is needed that initially combines the expertise of machine learning, user interaction, crowdsourcing, collaboration engineering, embedded intelligence, collective systems, and education. In a second step, further contributions from fields such as security and psychology (and others) will become highly relevant.

We propose to realise the productivity tracking (ProTrack) system by means of technology from the field of collaborative interactive learning (CIL) [2]. ProTrack will be interactive since it is based on bi-directional communication (i.e. queries to the user as well as providing feedback), collaborative in the sense that it uses students, other students, and external sources such as the Internet for generation of knowledge, and learning in the sense that it continuously and autonomously acquires knowledge. However, since CIL is a recent research area, we further outline the resulting research challenges that have to be covered for finally realising a sophisticated ProTrack system.

The remainder of this article is organised as follows: Section II briefly summarises the concept of CIL. This is followed by a brief introduction to the task-interaction-collaboration

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taxonomy used in the field (Section III). Afterwards, Section IV presents the ProTrack system including a technical concept and challenges that need to be addressed by the field of CIL. Section V presents an overview of relevant contributions from the state-of-the-art. Finally, Section VI summarises the article and gives an outlook to future work.

II. Collaborative Interactive Learning

Collaborative Interactive Learning (CIL) is a recent research area that focuses on the development of a new generation of systems with *lifelong learning capabilities* to work in uncertain environments and it is grounded on a socio-technical system perspective (as, e.g., outlined in [8]) since humans and other systems determine critical success factors. Such CIL systems are

- *learning* in the sense that they are able to self-improve their own knowledge bases in a self-organised way and, moreover, even self-optimise regarding the techniques applied to reach this goal,
- *collaborative* in the sense that various humans and/or smart systems collaborate in that learning processes to master more or less complex tasks including tasks which they cannot cope with alone, and
- *interactive* in the sense that there is an information and knowledge flow not only from humans to the smart systems but also vice versa in various ways.

As a result, CIL systems are a particular instance of the broader class of self-adaptive and self-organising systems [3], since they have to act highly autonomous in uncertain environments in the sense that

- they assess their own knowledge to decide when this knowledge is not sufficient to cope with new kinds of situations arising at runtime,
- they connect to new information or knowledge sources (e.g. other smart systems and/or humans) and know which kind of information or knowledge they can obtain from which source,
- they initiate an interaction step to inquire for information or knowledge that they have realised they miss to act optimally,
- they assess the quality of information or knowledge sources and the quality, usefulness, topicality, etc. of information and knowledge they gather, and
- they exploit various machine learning mechanisms to increase their own knowledge, e.g., collaborative learning, semi-supervised learning, transfer learning, reinforcement learning, and active learning (cf. [4]).

In the field of CIL, we distinguish two areas:

- In the area of **dedicated collaborative interactive learning (D-CIL)**, learning processes are typically clearly defined (such as, e.g., in an industrial quality monitoring process), an involved group of humans can be termed to be domain experts (with differing degrees of expertise in the specific application field), this group is rather small, and the experts collaborate over a longer period of time (see [5] for details).
- In the area of **opportunistic collaborative interactive learning (O-CIL)**, we face large-scale collaboration of smart systems that use all kinds of information and knowledge, even if these sources are sporadically available or very uncertain (cf. [6]). Goals of learning in such systems are sometimes not clearly defined and there may be several goals that are possibly conflicting. Humans cannot necessarily be assumed to be experts regarding certain applications (see [7] for details).

III. Task-Interaction-Collaboration Taxonomy

The field of CIL as outlined above has its roots in the domain of self-adaptive and self-organising systems. However, the shift towards a collaboration between distributed autonomous systems and humans requires a socio-technical system design [8]. In the following section, we briefly summarise implications for these socio-technical collaboration mechanisms by summarising preliminary work in the field of collaboration engineering, see [9].

CIL systems will be able to cope with different forms of collaboration. Smart systems take over tasks previously performed by humans and thus, change labour markets. Consequently, a reallocation of work is arising, and new forms and opportunities of collaboration occur [10]. The idea of CIL will help to shape the future reallocation of work between humans and machines. To use knowledge sources such as other smart systems and/or humans in an efficient way to achieve results of high productivity, a classification scheme for a different form of the division of labour is needed. Therefore, we propose to classify tasks according to their complexity and assign them to a collaboration-interaction-type.

The taxonomy of tasks and interaction-collaboration-types aims to identify and classify typical tasks and opens directions to sketch the opportunities for future research (see Fig. 1) [9].

		Interaction-Collaboration Types		
		Machine-Machine	Machine-Human	Human-Human
Task-Complexity	Low	Knowledge Exploitation Tasks	Area of	untapped potentials
	Average		Knowledge Validation Tasks	
	High	Area of Arising Questions		Knowledge Creation Tasks

Fig. 1. Task-Interaction-Collaboration Taxonomy, see [9].

The taxonomy distinguishes between three generic levels of task complexity:

- *Low*: Smart systems refer to a correct solution space (ground truth). The smart systems are able to solve the task on their own.
- *Average*: Smart systems refer to a solution space that needs to be verified by humans.

- *High*: A solution space does not exist. Humans need to create a solution and thus, the truth.

The taxonomy distinguishes between three interaction-collaboration-types:

- *Machine-machine:* Machines collaborate to solve a task autonomously.
- *Machine-human:* Machines and humans solve a task together.
- *Human-human:* Humans collaborate to create a correct solution for a given task.

By interpreting the cells of the taxonomy, the idea is that CIL systems facilitate the collaboration and interaction among other systems and/or humans. To facilitate the collaboration, we propose to develop reference processes that service as reusable patterns and bundle the whole expertise to allow for solving a task (e.g. assignments, recommendations). This makes collaborative procedures of CIL systems reusable and increases the potential to adapt it to other tasks and domains.

IV. A PRODUCTIVITY TRACKING SYSTEM FOR STUDENTS

Regarding the previously introduced taxonomy, we focus on the interaction-collaboration types *Machine-Machine* and *Machine-Human* in the following and mostly neglect the *Human-Human* type. Furthermore, we conceptually consider tasks from all three complexity levels.

Understanding human behaviour patterns is among the most challenging tasks in machine learning. Putting such patterns in a larger context of long term developments and processes taking place in human life is an even more ambitious problem. As an instance of this problem, we consider the question what factors influence the academic performance of students at a university. Such factors can range from study timing (how long before the tests, at what times of the day, in what time chunks etc.), through the question of studying alone vs. in groups (what type of groups) to general lifestyle and work life balance aspects (sleep patterns, sports, social activities etc.). Many of those factors can in principle be detected using sensors in people's mobile devices, device usage logs (e.g. music, video etc.), and digital information such as electronic agendas, communication patterns, and requests to users' personal digital assistants. We propose to use the CIL paradigm to solve the problem of relating such information to the relevant behaviours and behaviour patterns of users and to use the detected patterns to predict the academic performance of students.

To this end, we will proceed in two stages: We will consider (1) the problem of detecting behaviours and behaviour patterns and (2) the problem of predicting academic performance from such patterns, separately. In doing so, we will initially work on the analysis of the gathered data (incl. the processing of analysis results for students), where O-CIL and D-CIL work separately and are combined afterwards. Finally, we will include predictions, recommendations, etc. In terms of an experimental approach, we propose to substantially leverage APPs such as the TU-Kaiserslautern University APP [11] which has been developed by one of our groups as means for data collection with volunteer students. However, the APP provides just the basic functionality and needs novel components for CIL activities.

A. A productivity tracker for students

Technically, the basis for ProTrack will be the TU KL-APP that serves as official APP of the University and is increasingly popular with students. The APP is based on a general framework for participatory data collection that has been originally developed for large scale crowd monitoring [11] in the SOCIONICAL EU project and used by nearly $100,000$ people across Europe at various events [12]. Currently, systems based on the framework also include a participatory APP for tracking disease spread[1] and the visitors APP for an exhibition at the Pfalzgalerie in Kaiserslautern. We will use the framework to embed the O-CIL and D-CIL based data collection, the collaborative model building, and an exemplary academic performance prediction functionality into the TU-KL APP resulting in the envisioned Productivity Tracker System (ProTrack). We aim at recruiting student volunteers who will install and run the extensions over an extended period of time.

In the following paragraphs, we outline the schematic concept of the Productivity Tracker (ProTrack). ProTrack runs as APP on the students' smartphones and is connected to the university information system, external secondary users (e.g. lecturers), and other instances of the APP running on smartphones of students of the peer group. Fig. 2 briefly summarises the architecture.

1) Self-assessment: In general, there are two approaches to acquire direct feedback from students: questionnaires and label requests. The former approach is based on a standardised form that has to be completed in periodic cycles for rating personal feelings. Examples for the requested categories include level of stress, the current mood, the physical stress level, or the overall activity level. The second aspect, i.e. label requests, mainly comprises a module for active learning [13]. Here, the ProTrack system asks the student direct questions such as "Are you tired at the moment?" or "Are you working on the worksheet for the lab course?" (in general, there is always a certain trigger for these questions, i.e. a guess or an event). Asking the user directly provides knowledge with the highest reliability but, in turn, has to be utilised efficiently to avoid annoying the student and consequently decreasing his/her willingness to participate in ProTrack. The feedback then allows to generate and refine models for user behaviour and academic performance.

2) Activity classification: As a ubiquitously available source of monitoring the user behaviour, the various sensors of the smartphone are available. Examples include accelerometer, microphone, light sensor, GPS/Bluetooth, and WiFi (phone usage, website classification). Based on these sensor readings, activity recognition can be performed that assesses the current user behaviour (e.g. sitting, walking, running) and the corresponding higher-levelled context (e.g. attending a lecture

[1] See https://de.grippenet.ch (last access 09-01-2018)

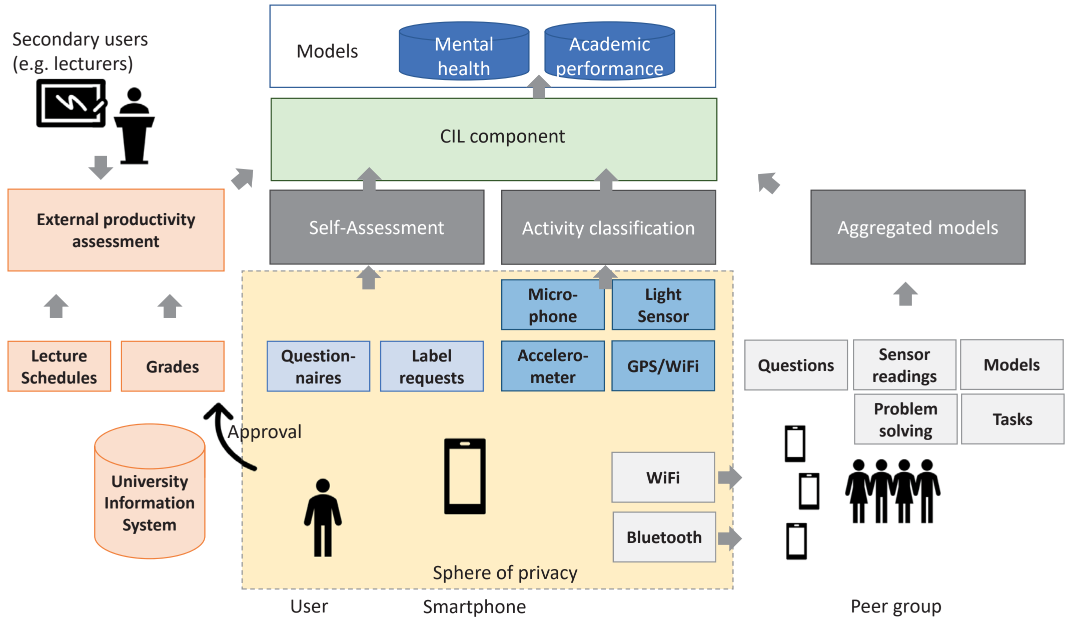

Fig. 2. Schematic illustration of ProTrack APP including the sensing and analytics system architecture.

or learning). However, especially the higher-levelled context information needs further external input (e.g. location information about lecture halls or status from other smartphones in the vicinity) to be able to come up with appropriate classifications.

3) Peer group: Besides the user himself, his/her fellow classmates are a valuable source of knowledge for monitoring and assessing the academic performance and the behaviour of the user. In Fig. 2, direct connection via WiFi and/or Bluetooth is envisioned. Here, questions, tasks/problem solving, sensor readings, and models built for the individual user or his/her classmates can be exchanged considering privacy concerns. Sensor information can be used to validate activity recognition measures, for instance. Exchange of models refers to higher-level knowledge such as expected learning times. In turn, the term "questions" can comprise direct questions for labels (as needed for active learning mechanisms such as "Are you cooperatively working on the same worksheet for the lecture?") that immediately are expected to be answered and questionnaires with a collection of aspects rating the behaviour of the particular student with a longer time horizon (and no immediately needed answer). This aspect especially demands for insights from the domains of crowdsourcing and collaboration engineering.

4) University information system: The detection of activities may benefit from additional context information such as the schedule of lectures and laboratories during the study period. This information is available through external sources such as the university information system and – besides topic and time – includes room numbers and scope (i.e. degree course, expected number of participants, and required prior knowledge). Furthermore, grades may be accessed when implicitly triggered by the user to provide the basis of calculating correlations between recognised behaviour and the resulting academic success.

5) Sphere of privacy: As outlined in the previous paragraphs, an exchange of knowledge and observations is substantial part of the ProTrack system. However, this exchange refers to a high degree to private data. Consequently, we envision to found ProTrack on concepts from the domain of federated learning (FL) [14]. The concept of FL comprises centralised components, and the decentralised autonomous entities (here: the users' ProTrack APPs) send model updates to these centralised components (and vice versa). All submitted content is checked for privacy issues prior to sending, and only appropriately anonymised information is shared. Corresponding mechanisms need to become part of the ProTrack system.

6) External productivity assessment: Academic performance can be measured in terms of success rates for courses. For instance, the student's semester-wise exam grades define how successful the last six months have been. This includes the degrees as well as the number of successful courses. In addition, secondary users such as lecturers or tutors may be queried about estimations of expertise, efforts, and understanding (although these measures are highly subjective) which can be considered in the overall models.

7) Models: The overall goal of the ProTrack system is to generate and maintain models as basis for predicting and explaining user behaviour. This comprises two major aspects: the academic performance and the mental health status that is interwoven with the academic performance aspect as highlighted in the motivation. Furthermore, a prerequisite for both are fundamental models for the expected behaviour of the students and their expected academic behaviour (i.e. a "semester model"); especially the expected academic behaviour significantly changes from semester to semester due to different lecture schedules. Furthermore, models generated and

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provided by other peers are combined with the own models.

8) CIL component: The major control unit for the ProTrack system is the CIL component that queries, gathers, and analyses incoming data at all abstraction levels and maintains the models. Since CIL is a recent research field, the major research efforts have to be done here, see Section II. In future work, the CIL component may augmented with capabilities for recommending the student study schedules and organisation of daily activities. We outline some of the resulting challenges in the following paragraphs.

B. Challenges for CIL

The ProTrack system covers aspects from both fields of CIL: D-CIL and O-CIL. In the following paragraphs, we outline the particular challenges for both fields.

The **D-CIL** part relies on smartphone based interactive questionnaires and tasks as well as online information such as lecture schedules. The system will accompany a group of students, tutors, and lecturers (e.g. a class of computer science students) over several semesters and actively capture and analyse the students' behaviour and life style by means of various kinds of questions. It will also be able to give some feedback by comparing the individual's behaviour to that of the group. Technically, this combines technology from several fields of research: (1) active learning [13] concepts to decide which information is triggered efficiently from the user, (2) collaboration engineering [15] and crowdsourcing concepts [16], [17] to provide appropriate and efficient collaboration with other user and their devices, (3) Organic Computing concepts [3] for system architecture and self-* mechanisms, (4) machine learning aspects such as sensor/information fusion, incomplete data handling, or transfer learning, and (5) meta learning [4] concepts to decide about the most beneficial utilisation of available knowledge sources.

The **O-CIL** part will be based on auditory scene analysis to recognise and assess situations that are relevant for productivity tracking. Recognising situations such as various learning settings, different leisure activities, social interactions, and other life style relevant factors is a well known problem in the research area of sensor based context and human activity recognition. Concerning STEM (science, technology, engineering, and mathematics)-disciplines we track, for example, also the weekly recitations and analyse how students solve the different tasks, how successful they are and which kind of strategies would be most suitable. This data will provide further suitable information to recommend successful learning strategies individually.

Today, the distinction between state of the art and open research problems runs along two dimensions: On the one hand, this refers to the complexity of the involved situations and activities and, on the other hand, to the degree to which the environment in which the recognition is taking place can be considered to be "open ended" rather than constrained and controlled. Thus, in sufficiently constrained lab environments with elaborate sensory instrumentation, various complex activity recognition tasks were demonstrated. For example, we have been able to show that a combination of eye motion tracking and head motion pattern analysis can be used to reliably distinguish activities such as reading, watching video, solving mathematical problems, or doing wood workshop tasks [18]. Furthermore, we could analyse cognitive state measurements on learning materials [19] and provide different kinds of learning support [20]. However, this has been accomplished in a lab setting with users sitting at a desk (no other motion artifacts) and engaging only in activities from a pre-defined setup. How this sort of recognition scales to dynamic, unconstrained environments is an open question. The practicability of well defined, stable head mounted sensor setups for continuous use may become another important issue.

For ProTrack, we propose to rely on a combination of two sensing modalities that are known to work well in every day life: location and sound, later possibly extended with user motions (from smart phone accelerometers) and presence of Bluetooth devices in the environment [21]. Indoor location based on the reachability of WiFi access points is already provided by most smartphone location services. Interestingly, the corresponding maps have been generated using a methodology reassembling a simple version of the O-CIL concept: from traces and WiFi scans voluntarily provided by users.

Audio signals are known to be a rich and reliable source of information about the environment and their use has been already explored in context and situation recognition [22]. In past work, complex audio context has been recognised with little computational effort [23]. In addition, it has also been demonstrated how privacy concerns can be overcome by recording only short snippets of sound (e.g. 100 ms every 0.5 sec) and randomly mixing them. While this makes the reconstruction of understandable speech impossible (which is the key privacy concerns), most relevant situation characteristics (e.g. the sound of a projector, the fact that a single person is speaking, music, cocktail party effect) can still be retrieved. The main problem preventing widespread use of sound as context recognition sensor for unconstrained environments is the combination of very high degree of diversity and the difficulty of gathering labelled sound data from real life environments. Thus, for example, while humans will easily recognise the humming sound of a projector in a seminar room, different projectors in different rooms do sound differently. Furthermore, different locations will have the projector sound overlayed with different background sounds, echo, etc. Statistical models built using the traditional method of recording sound from a set of devices and situations created in constrained laboratory environments have proven to be inadequate to deal with such real world variations. Instead, we propose to use the O-CIL concept to collaboratively, incrementally build such models from data collected on every day basis by smartphones of participating users. The system will exchange model components, labels, and training data between the users devices (and centralised components) in a way that maximises training progress while observing individual privacy policies, minimising resource usage and the inconvenience caused by label requests. We also have to investigate the use of online

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videos to be annotated by volunteers (e.g. through mechanical turk [24]) as an additional source of labels for training data.

V. Related work and research activities

This section describes the state of the art in some related fields. We distinguish between three relevant fields: (a) productivity tracking systems, (b) smartphone-based sensing systems, and (c) research areas relevant for basic CIL technology.

A. Productivity tracking

Directly comparable to the presented approach to productivity tracking is the StudentLife (SL) system developed at Dartmouth College since 2014, see [25]. SL is based on a continuous sensing APP that monitors students' activities and assesses the day- and week-based impact of cognitive load on stress, sleep, activity, mood, sociability, mental well-being, and academic performance. The study was performed with 48 students for 10 weeks using Android phones. Analysis and evaluation of the gathered data showed a number of significant correlations between the objective sensor data from smartphones and mental health and educational outcomes of the student body. Furthermore, a certain Dartmouth term lifecycle has been found in this data: students are typically starting the semester with high positive affect and conversation levels, low stress, and healthy sleep and daily activity patterns. With increasing workload induced by ongoing study programmes, stress appreciably rises while positive affect, sleep, conversation and activity drops off. Afterwards, SL has been used for further investigations in the field resulting in the SmartGPA system [26], which promises to distinguish between study (e.g. study duration) and social (e.g. partying) behaviour of a group of undergraduates. The SL approach slightly differs in the scope and the basic information gathered by the smartphones. It further can be improved by CIL technology by means of allowing for active collaboration between machine and humans or groups of these. However, it illustrates that ProTrack is feasible and may result in the expected results.

Almost in parallel to SL, Watanabe et al. [27], [28] used sensor badges to track student activity. They focused on the correlations between scholastic performance and face-to-face interaction among students during break times. Compared to SL and ProTrack, the sensor equipment is limited and the scope is restricted to face-to-face interaction.

Besides technical solutions, contributions from the fields of education and psychology provide the theoretical foundation of the ProTrack approach. Here, research has investigated which aspects can be used as appropriate predictors of college students' academic performance. The main focus was on students' personality traits (e.g. conscientiousness), their lifestyle behaviours (e.g. sport activity, social activity, sleeping behaviour), and mental states (e.g. stress, attraction) and the correlation of these aspects with the course grades. For a recent survey in this field, see [29]. Other studies revealed that aspects situated in the students' personality have a major impact on the academic productivity and success [30], [31]. Furthermore, grade averages tend to be higher among students meeting health guidelines for moderate–vigorous physical activity [32], [1]. Although being difficult to study, social interaction behaviour seems to be a further highly relevant aspect for students' productivity in academia [33].

B. Smartphone- and sensor-based monitoring systems

Besides productivity aspects, smartphone-based recognition of mental states is closely related to the scope of ProTrack. For instance, [34] considers wearable sensors to assess the physical and mental state of test subjects. In particular, a group of eight senior persons has been investigated living in a continuing care retirement community. The study was performed for one week and revealed a correlation between depression and patterns in the measured sensor data. As an alternative, [35] used wearable sensors again and focused on bipolar disorder – but long-term data is missing from this study. Other studies correlated self-assessment of users with sensor data, see e.g. [36], [37]. The results indicate that self-reported activity, stress, sleep and phone usage are strongly correlated with self-reported mood.

Further systems focus on interfaces for mental health service providers to observe the state of a patient. Examples include Health Buddy [38] and Mobilyze [39]. However, these systems are only applicable to a specific use case and are based on a predefined set of questions/answers or triggers.

C. Collaborative interactive learning

As outlined in Section III, CIL is a recent research area that has its roots in several domains. In the following, we briefly summarise the most relevant fields and their benefit for CIL.

Fundamentals of Collective Adaptive Systems investigates design and operation principles for heterogeneous, distributed systems with entities that have individual goals and solution strategies [40]. These entities interact at various temporal and spatial levels. A key aspect is the cooperation of humans with systems. Important issues are conflict resolution, long-term stability, handling noisy or outdated information, and development of open systems where single entities leave the overall system and new ones enter.

Multi-Agent Systems (MAS) is a field concerned with design and cooperation schemes for distributed collections of autonomous subsystems [41]. In this context, an autonomous subsystem is called "agent" since it acts on behalf of a certain user and aims at achieving the predefined goals of this user. Conceptually, the term MAS summarises research on questions in the context of how autonomous, distributed, and smart agents can share their knowledge and experience, negotiate their goals, and develop plans based on their potentially heterogeneous capabilities, resulting in coordinated actions and collective problem solving. These aspects provide a valuable basis for ProTrack in particular and CIL in general – however, questions of modelling the knowledge or novel crowd-oriented interaction patterns have to be developed.

Online Learning (OL) algorithms process data which arrive in a sequential order [42]. They aim at learning knowledge incrementally from past data. This is especially important in situations with huge amounts of data which cannot be stored or processed in feasible time (big data). More advanced methods are able to react to drift or sudden shift in time-variant data streams or are combined with active learning.

Organic Computing (OC) [3], [43] (see also Autonomic Computing [44]) addresses complex technical systems that will self-adapt to new environmental conditions at runtime. Key technologies are self-$*$ techniques inspired by nature (e.g. self-configuration, self-organisation, or self-optimisation). By means of such self-$*$ mechanisms, traditional design-time decisions are shifted to runtime and into the responsibility of systems themselves, resulting in a massively increased autonomy [45], [46]. In the context of ProTrack and CIL, OC will provide basic technology – however, the approaches from the fields lack fundamental research on collaborative learning approaches (in particular active learning approaches) allowing for an adaptation to emerging environmental situations in time-variant environments as outlined for ProTrack [2].

Activity Recognition aims at deriving high level knowledge about human activities and the situation in the human's environment from simple sensors. Sensorial data can be provided by mobile motion sensors (e.g. accelerometer). In some cases, further sources from other applications or domains that provide higher level information such as calendars or statistics (for instance, time usage statistics or computer usage statistics) are used as well. In the recognition process, the sensor data are processed and matched to activities. The continuously incoming data stream is segmented, for instance by applying a Sliding Window or Sliding Window And Bottom-up (SWAB) approach [47]. For each segment application-specific characteristics, i.e. features, are extracted. Commonly extracted features are statistical features (e.g. mean and variance) or energy [48]. These features are often used as they are easy to calculate and simultaneously provide additional insights into the data characteristics. Furthermore, features calculated in the frequency domain have been investigated. The analysis of time series data in the frequency domain can extract unseen patterns and trends in data [49]. For example, a Fourier transform can be used to uncover data characteristics that support the recognition of a user's fall [50]. The extracted feature values are passed to a machine learning algorithm to generate an AR model. A variety of machine learning algorithms are available such as decision trees, Support Vector Machines (SVMs), or Bayesian classifiers. The generated model identifies a user's activity based on the incoming feature values. Finally, recent work focused on self-adaptation of sensor constellations for activity recognition [51], [52].

VI. Conclusion

In this article, we motivated the need of novel productivity tracking tools for observing and continuously analysing the academic performance of students. Such a tool is envisioned to provide a basis for self-improving the academic behaviour of students and consequently reduce drop-out rates. We presented a first concept for such a tool based on available campus APPs and highlighted the need of research in the field to finally come up with a successful solution.

Due to the distributed and time-variant nature of the system as well as the underlying dynamics and heterogeneity of users, we motivated that a solution can be found in the combination of technology from the field of collaborative interactive learning (CIL) with other related fields such as Organic Computing, crowdsourcing, and collaboration engineering. We distinguished between two main areas of research, namely dedicated and opportunistic CIL, that have to be addressed for finally realising the productivity tracking system (ProTrack). We outlined the corresponding research challenges which we have to address to develop a CIL-based ProTrack system.

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