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Learning Analytic Tools for Massive Open Online Courses

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Affidavit

I declare that I have authored this thesis independently, that I have not used other than the declared sources/resources, and that I have explicitly indicated all material which has been quoted either literally or by content from the sources used. The text document uploaded to TUGRAZonline is identical to the present master's thesis.

Date

Signature

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Abstract

Massive Open Online Courses (MOOCs) provide anyone with internet access with the chance to study at university level for free. In such new emerging learning environments, learners produce vast amounts of data representing their learning process. Learning Analytics can help identifying, quantifying and understanding these data traces which is what motivated this thesis.

Basic metrics to capture the learners' activity are aggregated in an approach of behavioural analysis. Within the tool LA Cockpit, the addition of web analytics is paired with state-of-the-art visualization techniques to build a dashboard. This dashboard contains interactive widgets which let the user explore their datasets themselves and improve their understanding of the underlying key figures and help them generate actionable insights from the data.

The implementation of the Web Analytics Plugin shows that learning analytic dashboards provide a suitable tool to bridge the distant nature of learning in MOOCs. Together with the extendible design of the LA Cockpit is a future-proof framework to be reused and improved over time. It shows that different metrics can improve insight and understanding of the way learners consume learning content. With this additional feedback on the learners' behaviour within the course, it will become easier to improve the learning process by tailoring the provided content to the online learning community.

Kurzfassung

Massive Open Online Courses (MOOCs) bieten heutzutage jeder Person mit Internetzugang die Möglichkeit, auf Universitätsniveau zu lernen, und das kostenfrei. In solchen neu aufkommenden Lernumgebungen produzieren die Lernenden große Datenmengen als Abbild ihres Lernprozesses. Mit Hilfe von Learning Analytics können diese Daten identifiziert, quantifiziert und dargestellt werden.

Um die Lernaktivität einzufangen und abzubilden, werden verhaltensbezogene Daten aggregiert und grundlegende Metriken definiert. Innerhalb der Software LA Cockpit wird diese zusätzliche Funktionalität der Web Analyse als sogenanntes "WA Plugin" mit aktuellsten Visualisierungstechniken zu einem Dashboard kombiniert. Interaktive Widgets bieten den BenutzerInnen die Möglichkeit, Datensätze selbst zu erforschen und ihr Verständnis der zugrundeliegenden Information zu verbessern. In Folge helfen diese Widgets Lehrenden, umsetzbare Erkenntnisse abzuleiten.

Die Implementierung des WA Plugin zeigt, dass Learning Analytic Dashboards ein geeignetes Werkzeug sind, um die Brücke zwischen LehrerInnen und Lernenden, die durch das Lernen auf Distanz in MOOCs entsteht, zu schlagen. Zusammen mit dem erweiterbaren Konzept des LA Cockpit bietet das Plugin eine zukunftssichere Software-Basis. Die definierten Metriken unterstützen BenutzerInnen der Software bisher nicht sichtbare Zusammenhänge erkennen zu können, oder besseres Verständnis über die Art und Weise, wie Lerninhalte konsumiert werden, zu gewinnen.

Dank dieses zusätzlichen Feedbacks des WA Plugin ist es zukünftig einfacher, den Lernprozess zu verbessern, da die Lerninhalte und ihre Präsentation effizient an die Lernenden und deren Bedürfnisse angepasst werden können.

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1. Introduction

One constant thing in our lives we will do from the day we are born is learning. We start out as children making our first steps and continue to learn basics such as reading and writing in elementary school. Some choose a path of higher education where they focus on their fields of interest followed by deeper research. The Oxford Dictionary defines the term learning as the "the acquisition of knowledge or skills through study, experience, or being taught."¹ However, learning does not solely happen while physically being in educational institutions, it is heavily shaped by our environment, be it in the attitude or the access we have towards its resources.

Supported by current means of technology, we see a change in the way how learning takes place. In the ubiquitous learning environments we all currently live in, the internet as a provider for information and educational material plays a central role, changing the field of education. In its initial function as an open and decentralized network the internet inspires its applications with best examples of open source software or open learning environments. Labelled as the future of education [5], Massive Open Online Courses (MOOCs), gained traction over the last decade. MOOCs scale well for a large audience and offer in their basic idea free learning content to everyone with access to the internet. Being commonly considered the first MOOC, the course called "Connectivism and Connectivist Knowledge" held in 2008 by Downes and Siemens marked the start of a steady rise, especially from 2012 on, of courses offered on online distance learning environments [44].

¹<https://en.oxforddictionaries.com/definition/learning>,
last accessed: February 10, 2019

1. Introduction

The legitimate next step when seeing new environments enthusiastically being applied, is to observe and analyse them, to grasp and understand this new way of learning and improve the underlying process. In this intersection of various academic fields, for example education, psychology, pedagogy, statistics, machine learning and computer science a new term was coined: Learning Analytics [12]. In 2011, the Society for Learning Analytics and Research² (SoLAR) defined Learning Analytics as “the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environment in which it occurs” [37].

Two main ideas dominate the field of Learning Analytics research: first, to understand learning itself and the environments in which learning occurs [56]. Second, the approach to optimize these factors. Using the gained knowledge to improve the inherent learning environment is a very intuitive one. Clow [11] investigated this concept of closing the feedback loop in his research 2012. Another idea on how improvements can be handled was proposed by Khalil and Ebner [34], who introduced a Learning Analytics life cycle, depicted in figure 1.1.

In this cycle four main phases are identified. Learners inevitably produce data when engaging with their learning environment. This process gets represented and stored as massive dataset, referred to as Big Data in the figure. Following this, the next step, Analytics, is needed to interpret these traces of learners behaviour and make sense of it. In the middle of these four steps, interconnecting all aspects, the tools for Learning Analytics are placed. This cycle needs to be taken into account when designing and implementing a Learning Analytics tool and none of these aspects should be neglected.

When thinking about Learning Analytics research and applying its tools one needs to consider the people using it. There are different interests and benefits one can draw from and the interested stakeholders can be categorized into various groups. Leitner et al. [41] use the following three stakeholders: Researchers/Administrators, Learners and Teachers. Each

²<https://solaresearch.org/>, last accessed: January 22, 2019

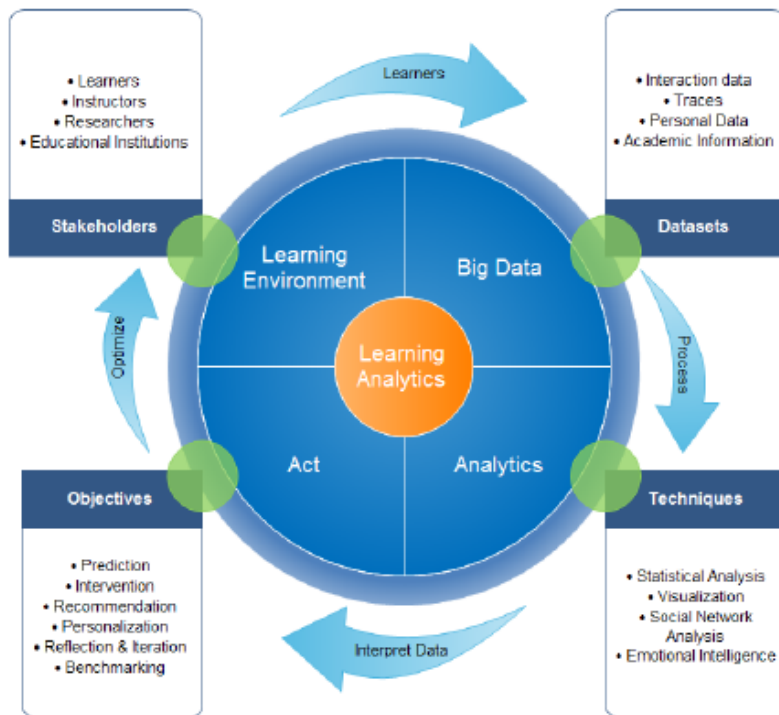


Figure 1.1.: Learning Analytics Cycle [34]

group has their own motivation and interest in using Learning Analytics, though these are not mutually exclusive, the benefits these groups can draw from, are neither. Especially in the field of higher education (HE) the idea of analytics together with already known tools of business intelligence proved popular with administrators and the institutions they work for [19]. Despite the target audience, Learning Analytics itself should follow guidelines and have clearly defined goals and benefits for any stakeholder [29].

One important take away from research conducted up until now should be that there can be no "one-size-fits-all" Learning Analytics solution [8]. A careful approach when designing and implementing tools, preceded by a requirement analysis of the involved stakeholders, university or platform guarantee a successful deployment and valuable output.

1. Introduction

The datasets for Learning Analytics conveniently directly stem from the deployed learning management system, where statistics such as number of downloads or accesses into the system can be generated. Being stored as log files or plain figures, this information and its sparse representation might not be enough when the research question is to determine, how learners put MOOCs into use and how to represent their learning process.

To receive a human interpretable representation, a chain of steps is necessary, from identification what traces learners leave, via techniques of data aggregation within this learning environment through to data modelling and definition of key figures and metrics [15].

The Web Analytics Plugin, presented in this thesis, iterates over these steps, by capturing learner's interaction with the provided resources in online accessible courses on the Austrian MOOC platform imoox.at. Furthermore, suitable metrics to be presented to the stakeholders are defined. These are encapsulated as widgets and integrated within a Learning Analytics tool and dashboard visualisation.

This approach provides the chance for a differentiated view on how learners interact with learning material within MOOCs. As a quick way to deduce points of interest, the behavioural analysis and its metrics can help teachers transfer their knowledge from face-to-face classroom situations to new online learning environments. Combined with the educator's experience, such visualizations support the inspection and decision process on where to act and improve the learning process.

With guidelines and best practices in mind from deploying the Learning Analytics Cockpit (LA Cockpit) [43], this thesis aims to provide an addition to the framework in form of another plugin, called "Web Analytics Plugin (WA Plugin)". It shall bridge the information gap teachers in MOOCs face compared to real life classroom learning situations. The plugin explores what can be inferred from recorded activity traces in online learning environments. For integration within the existing framework, a subset of possible metrics is designed, on which the plugin explores suitable means of visualizations for captured learners engagement and behaviour. Web Analytics of online learning courses aims to provide data-driven

insights so teachers can assess the acceptance, activity and quality of their courses within the distant learning environment. The plugin should provide means of evaluation to allow improvements in the quality of the offered MOOCs by tailoring the contents and presentation towards the MOOC Community.

The thesis is organized as follows. The background of Learning Analytics and its distinction to related terms such as academic analytics or educational data mining is given, especially in the context of higher education and Massive Open Online Courses. Due to the interdisciplinary nature of the research area connections to other fields of science and their importance are discussed. Background analysis of the technological and social environment of behavioural analysis and the WA Plugin's concept and design strategy and its refinements through development phases are given and discussed in more detail. Subsequently, implementation details are shared. Proof of concept for the WA Plugin in the MOOC environment "iMooX" and feedback is discussed, which leads to outlook on further work and concludes future possible improvements on the Learning Analytics framework.

2. Background

In our daily interaction with inter(net)connected devices a constant stream of data is produced, recorded and stored for later use. This involves analysis by the devices and platforms we use, quantifying our actions with the well known promise of improving our shopping experience or faster and more personalized search results. The extraction and description of what data is useful is an essential question, already discussed by Baepler 2010 [4]. Nowadays this assessment is still central to the scientific community, with increasing data, the dimension of tools, services and time used.

In the field of Learning Analytics, researchers face additional challenges besides an abundance of data. Learning does not happen at one specific point in time or in one particular place. It is a process we are constantly going through, throughout our daily lives, most prominently in what we call education. Traditionally, educational institutions hold the resources for learning, but in the 21st century there is no need to confine anyone to only these options. Educational resources, lexicons, online discussion forums or video lecture courses are becoming openly available to everyone provided decent internet connection is available. The next section will explain the specific context of learning with online courses geared towards a large audience.

2. Background

2.1. Massive Open Online Courses

Beyond looking up terms and definitions, many learners actively join learning communities online when educating themselves. Massive Open Online Courses (MOOCs) are a characteristic of this movement emerging within the last decade. The term was coined by Bryan Alexander and Dave Cormier when referring to the course "Connectivism and Connective Knowledge (CCKo8)". From 2012 on the concept received even broader attention [24], especially thanks to the widely acknowledged online course of Sebastian Thrun and Peter Norvig (Stanford University) "Introduction to Artificial Intelligence". This is currently still an available and popular example of a Massive Open Online Course with many active new learners joining every day.

The familiar image of MOOCs in the broader public audience are online platforms providing learning material in a course-structured format. A webpage could display current course news, course updates or messages from the lecturers, recently added material or new forum posts. Links to course content, which is taught via video material are provided, and uploading assignments in a regular timely fashion as well as quizzes for self assessment are available [37].

This branch or type of MOOCs, with a lecture oriented approach, is referred to as xMOOC by most literature. Two main categories of courses can be identified: xMOOCs and cMOOCs. The first are defined to be individualistic, using classic e-learning platforms and are based on resources. Whereas the second type, cMOOCs, are considered connectivist and based on social learning, cooperation and use of web 2.0 [21]. Another way to differentiate between those two is to look at the participants involved. These can unambiguously defined as either teachers or learners in xMOOCs, whereas each individual is considered to incorporate both roles in cMOOCs. Of course there are many more models in addition to those two categories. Many mixed variants of MOOCs try to overcome the individual drawbacks and provide a profound learning experience by combining features and approaches (see table 2.1).

2.1. Massive Open Online Courses

	cMOOC	xMOOC
Learning Model	connectivist	classic
Objectives	build by participants	build by teacher
Learning	navigate, build community	follow the course
Resources	aggregation by participants	provided by the course
Interactions	external and distributed	on site, centralized

Table 2.1.: Distinction between cMOOC and xMOOC [21]

The general hype around MOOCs became evident when 2012 was deemed "the year of the MOOC" by the New York Times in the article by Laura Pappano [46]. 2012 was also the year today's major platforms Coursera¹ and edX² were founded. Since then a large variety of platforms (commercial as well as non-commercial) for learners to choose from, some specializing on certain topics such as Codecademy³ or Khan Academy⁴, has emerged. The MOOC aggregator website Class Central⁵ lists the top five MOOC providers according to the number of registered users in their yearly report⁶. These numbers from 2018 show the broad general acceptance and curiosity of with registered learners worldwide:

1. Coursera - 37 million
2. edX - 18 million
3. XuetangX - 14 million
4. Udacity - 10 million
5. FutureLearn - 8.7 million

¹<https://www.coursera.org/>, last accessed: 23, 2019

²<https://www.edx.org/about-us>, last accessed: January 23, 2019

³<https://www.codecademy.com/>, last accessed: January 23, 2019

⁴<https://khanacademy.org/>, last accessed: January 23, 2019

⁵<https://www.class-central.com/>, last accessed: January 23, 2019

⁶<https://www.class-central.com/report/mooc-stats-2018/>, last accessed: January 23, 2019

2. Background

MOOCs can be seen as a special form of online courses with a strong focus on interaction and integration of various technologies such as videos, forum discussions or quizzes to provide a stimulating learning environment. Therefore they offer specific benefits and certain drawbacks which will be discussed in the next section.

2.1.1. Possible Benefits

An often cited benefit of MOOCs, tightly connected to their origin, is the access to higher education for millions of people given their access to the internet [31]. Generally designed without credits and only some loose formal certificate of attendance this has become a recent business model. Participants can pay to get official confirmation of completed courses. These course credits are accepted by certain partner universities, depending on the MOOC platform, and allow enrolled students to complete parts of their curriculum via MOOCs. For everyone else they still raise the education level and support learners with content otherwise not accessible. In the spirit of openness, most of the courses are offered free of charge, meaning access without registration fees or subscriptions. The flexibility in consuming learning content, so the chance to learn anywhere or anytime, e.g. accessing recorded lectures whilst commuting, is appealing. This argument leads universities to use MOOCs to support their traditional courses in a so called blended learning approach [13], [45]. This can help to overcome scarce resources such as lecture halls or time constraints in student's curricula.

Self paced learning gives learners the time to review some lectures or skip over parts they are already familiar with. Self paced also means that there is no mandatory time schedule the learners need to adopt. Due to their stricter organizational structure, however, most of the xMOOCs follow a certain time frame and schedule. Within that time frame, especially if homework or additional tasks are required, the course is open for registration and allows for grading, personal feedback and discussion with teaching staff available for the MOOC participants.

2.1.2. Challenges

Learners are very used to the personal teacher connection in real life, but in online learning communities, language barriers, translation errors and resulting misinformation could subsequently lead to misunderstandings which in turn can lead to a lack of foundations of the learning content. Time and effort required are often underestimated from attendees and lead to a declining motivation and consistency to regularly commit to an online course [10]. Attendees are required to have a high level of self-regulation and clear idea of their goals. The generally low retention rates [25], [33] are a big issue and under active research. Common contributing factors to that phenomenon need to be identified and improvements, wherever necessary, need to be made, eventually in order to get more attendees to finish their started courses.

2.2. iMooX

Massive Open Online courses as a new addition to universities' educational strategies can enrich lectures. Institutions benefit from joint resources on centralized platforms and a potentially bigger audience to their lecture content. Austria's first and only MOOC platform, iMooX⁷ was created in 2013 by University of Graz and Graz University of Technology (the partnering institutions are also stated on the login screen of the platform, figure 2.1). It offers free online courses on a variety of topics, all free of charge. There is a strong focus on open resources throughout all courses, which means that the content and materials can be used without concerns due to the Creative Commons⁸ license.

Currently (February 2019), there are more than 40 courses on the platform, ranging from "Progamming for children with Pocket Code" to so called "bridging courses" (helping soon-to-be university students transitioning

⁷<https://www.imoox.at>, last accessed: January 29, 2019

⁸<https://creativecommons.org/>, last accessed: January 23, 2019

2. Background

from school to university level in e.g. Mathematics) up to well-attended blended learning courses from the partnering universities.



Figure 2.1.: Login Screen imoox.at, January 22, 2019

2.3. Learning in MOOCs

Literature refers to learning in virtual environments as technology-enhanced learning [35]. In the German-speaking world it is often used as synonym for e-learning and it also includes the topic of MOOCs. The concepts of traditional learning have changed with newly created technologies, but the foundations and knowledge of learning theory from pedagogy and psychology still apply. Learning theories can be seen as principles explaining how one acquires, retain and recalls knowledge and build a basic block in the domain knowledge of the technology related learning sciences.

The three main learning theories used in literature and adapted by scientists are: behaviourism, cognitivism and constructivism [18]. Advocates of each of these are distinguishable by their definition of what learning comprises and how learning happens. The most noticeable differences between those can be defined in the following way [1].

2.3. Learning in MOOCs

Behaviourism Learning is defined as new or changing behaviour. This is created by associating stimuli and responses. The change of behaviour is seen as the point at which learning occurs.

Cognitivism Learning happens through human information processing, which leads to understanding and retention of knowledge. This processing is necessary to be able to mirror and recall knowledge later on.

Constructivism Constructivism believes that one creates their own ideas and concepts based on prior knowledge - learning is creation and adjustment of such mental models by individual experience.

These models and their lack of transferability to modern technology lead Siemens in 2000 to his proposed additional theory of learning. He called it connectivism and discussed the experiences and results from applying network-like concepts of learning from his MOOC, CCKo8, in his work "Connectivism, A Learning Theory for the Digital Age" [50]. Critics (Kerr [32] or Kop & Hill [39]) challenge whether connectivism should be seen as learning theory or more as a pedagogical view on today's learning. Nevertheless they acknowledge the importance of network- and technological concepts due to the influence technology-enhanced learning environments have on today's society. In terms of MOOCs the two main types are often connected with two distinct learning theories, cMOOCs are considered to be more related to connectivism and xMOOC feature learning that falls into the learning category of behaviourism [50].

The need for learning theories becomes clear as soon as one tries to define benefits of tools or concepts. Desired outputs can only be modelled upon hypothesis and clearly defined inputs. The benefits of registering for a MOOC and participating have been discussed in section 2.1.1. Not only focusing on the participants' gain, one can ask how the other stakeholders (e.g. teachers) can benefit from providing MOOCs. Learning in MOOCs can be seen as applicable for all involved groups: it does not only involve students, but the providers and creators of such online courses as well.

2. Background

2.3.1. Teaching with MOOCs

The decision to offer a Massive Open Online course is succeeded by first rethinking the content and presentation of lecture content. Most often, lecture content evolves over the first few iterations, but after that, it is the easy choice to stick with what has proven to work. That is the pattern most experienced educators seem to follow [55]. MOOCs makes those educators rethink, because suddenly one is providing for a different audience with different means of communication. The new possibilities may result in restructuring or creating additional content. Second, educators might hesitate to adapt new technologies and fear the effort of transitioning to online courses. MOOCs and their surrounding participant's enthusiasm can be an incentive for all people involved pushing towards new means of teaching. Third, MOOCs can provide analytics for the learning community. One can evaluate how students use the provided course content. How effective are created learning materials by comparing e.g. the number of downloads? How are video lectures consumed? With Learning Analytics one can improve the speed and accuracy of such feedback. This feedback should go beyond grading schemes and provide insights into why a student selected the answer they did or identify patterns stemming from the learning process underneath. Only after being presented with additional information, the teacher can adjust lessons or exams and improve the quality and satisfaction within the online course. The principles of learning theories should be used as guidelines when designing educational content, but these serve as a good starting point for all tools that try to offer improvements.

The distant nature of MOOCs adds layers of uncertainty and questions all involved stakeholder have. Learning Analytics hopes to answer these questions. What this research field consists of and its aims and challenges are discussed in the following section.

2.4. Learning Analytics

Visually inspecting raw datasets is not an option when it comes to Massive Open Online Courses, with increasing amounts of data produced by the learners the need for Learning Analytics becomes evident.

The term Learning Analytics already suffered from term sprawl in the early beginnings of this research field. In 2011, Siemens and Long, [52] proposed definitions (figure 2.2), stating the different focus for the three often synonymously used terms Learning Analytics, Academic Analytics and Educational Data Mining.

TYPE OF ANALYTICS	LEVEL OR OBJECT OF ANALYSIS	WHO BENEFITS?
Learning Analytics	Course-level: social networks, conceptual development, discourse analysis, “intelligent curriculum”	Learners, faculty
	Departmental: predictive modeling, patterns of success/failure	Learners, faculty
Academic Analytics	Institutional: learner profiles, performance of academics, knowledge flow	Administrators, funders, marketing
	Regional (state/provincial): comparisons between systems	Funders, administrators
	National and International	National governments, education authorities

Figure 2.2.: Learning Analytics - Academic Analytics Distinction [52]

The distinction was made upon who benefits and steers the analytics:

Learning Analytics Learner will benefit, analysis on course level.

Academic Analytics Stronger focus on benefits for administrators and institutions.

Educational Data Mining Focus on predictive modelling, clustering and pattern mining.

2. Background

Especially educational data mining (EDM) can be seen as a toolset of information retrieval technologies, where data is used to generate models and predict on the available dataset, known from business intelligence approaches [4]. In this context a vast array of scientific tools are applied, ranging from e.g. knowledge discovery techniques, data mining until classification or artificial intelligence efforts.

Mentioned first in the Horizon Report 2012 [30], a converging definition for Learning Analytics has been defined as "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" [51], see figure 2.3. The research field has rapidly grown since 2012. The intertwined nature led researchers to the founding of the Society for Learning Analytics Research (SoLAR). It acts as a patron coordinating the annual instalment of the International Conference on Learning Analytics & Knowledge (LAK) and offering multiple initiatives to support collaborative and open research with regards to Learning Analytics. It promotes and consults with state, provincial, and national governments for the beneficial development of the research field⁹.

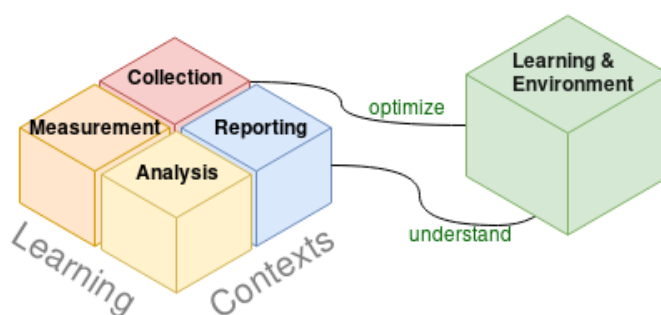


Figure 2.3.: Learning Analytics Definition

Referring back to the stakeholders interested in applying Learning Analytics, universities always have been a main force for research and application of new technologies.

⁹<https://solaresearch.org/about/>, last accessed: January 21, 2019

2.4. Learning Analytics

Especially Learning Analytics has started its hype in the field of higher education with major promises to identify “students-at-risk” and remedy the high drop-out rate. This early research focus were soon to be questioned e.g. by Gartner [54]. Learning Analytics cannot be seen as the single remedy for low completion rates, or as silver bullet against drop out rates. Ongoing research such by e.g. Khalil [33] shows, that Learning Analytics with the right indicators, however, can improve the learning process, which in turn can lead to decreasing drop-out rates.

In the field of MOOCs Learning Analytics is essential due to the massive and distant nature of the learning process. A lot of participants, many courses and limited teacher, administrators, time and resource budget are the obvious limitations in the learning process. The traditional approach to analyse, interpret and give individual feedback is not applicable in these environments. When LA gets tied into the process of teaching, which goes beyond delivering learning content, the benefits can be turned into actionable insights [10]. The connection between all stakeholders gets improved or re-enabled. With learning analytic tools each involved group gets the chance for self-reflection and thereby the chance for improvement. This can refer to the motivation of students as well as teaching resources or engagement in discussion forums on the online courses.

How to tie these analytics and insights into the learning process and especially how to transport the metrics in an easy human understandable fashion for the stakeholders is covered by research on Learning Analytics Visualization. It is suggested that visual displays are critical for sense-making because humans can only process large amounts of data if presented in meaningful ways [17]. Therefore, the next section will give a short overview of a common and suitable way to group the information and present it in a visually pleasing way.

2. Background

2.5. Learner Dashboards

The increase in educational data traces led researchers to reuse tested and proven tools from other research fields. Digital Dashboards as data visualization strategies use common presentation technologies such as charts, graphs or maps [17]. They have successfully been adapted with educational data [28], [8]. These learner dashboards can create an effective tool in capturing, visualizing and aiding teacher and learner to interpret and evaluate on metrics, processes and contexts of the learning process.

Based on earlier research as well as on lessons learned on how to design learning dashboards [40], [37] one can compile three reoccurring ideas:

Relevant metrics Choosing what metrics are relevant for the target group of the dashboard is a crucial step. Failing to do so clutters the tool or discourages the user. No additional value when applying Learning Analytics would be given.

Visuals Using the right colours and visualization types to convey what is not commonly seen and make complex coherences understandable is essential. Use basic principles of interface design to prohibit falsifying the aggregated data.

Interactivity Different views or filter options increase the user's utility of the tool and appeal to the curious nature of humans. Interactivity is favoured over given discontinuous numbers.

Together with the demand for providing online resources the question for applicable software arises. So called learning management systems (LMS) are the foundations for that, applications for administration, documentation and provisioning of online resources. There are various paid and free alternatives to choose from - either to self-host with own infrastructure or - currently emerging - as software-as-a-service cloud instances.

2.5. Learner Dashboards

In the open source category three popular (by their self-reported number of users) products one comes across: Moodle¹⁰, openEdx¹¹ (a product of edX) and Canvas¹².

All these applications provide basic logging capabilities and some basic visualization - but most often teachers and administrators are left with log files for specific metrics and key figures. The ideas and concepts from Learning Analytics get slowly picked up because of the additional effort in providing features beyond statistical figures and reports and high evaluation need for those tools. Specifically for Moodle there exist various dashboard plugins with learning analytic capabilities. Some integrate connections to external servers or advertise for their additional paid content. Two of the major examples here are Intelliboard¹³ and SmartKlass¹⁴. A screenshot of their start pages and their dashboard visualization are depicted in figure 2.4 and figure 2.5.

Smaller projects and plugins (such as Analytics Graphs¹⁵) are not applicable for a broad range of possible users. They either cover specific use cases or their implementation lacks the wide range of analytical features and customization options. Most of these plugins are geared towards a smaller subset of courses, administered by a single teacher and strongly mirror the university and course infrastructure they have been implemented for. The costs of adaption and transferring such tools do often not correlate with the possible outcome.

Big MOOC platforms such as edX provide dashboards for different stakeholders, student-facing as well as teacher-facing dashboard implementations. Figure 2.6 shows edX Insights, a dashboard which provides analytics specifically geared towards edX' role as MOOC provider.

¹⁰<https://www.moodle.org>, last accessed: February 02, 2019

¹¹<https://open.edx.org/about-open-edx>, last accessed: February 12, 2019

¹²<https://www.canvaslms.com/>, last accessed: February 09, 2019

¹³<https://intelliboard.net/>, last accessed: February 02, 2019

¹⁴https://moodle.org/plugins/local_smart_klass, last accessed: February 02, 2019

¹⁵https://moodle.org/plugins/block_analytics_graphs,
last accessed: February 11, 2019

2. Background

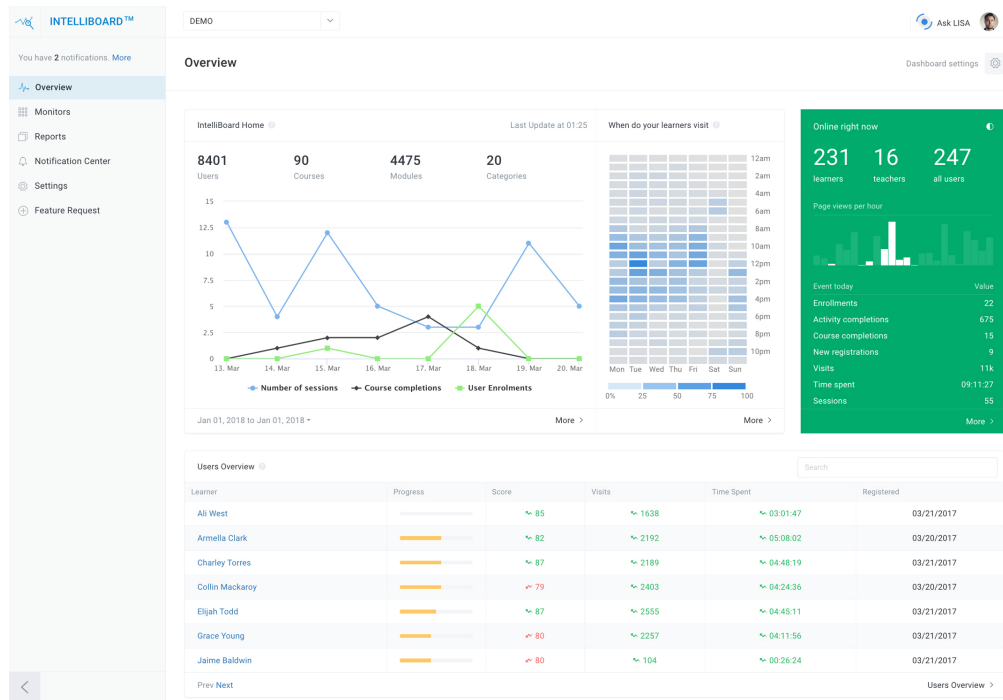


Figure 2.4.: Moodle Intelliboard Dashboard [27]

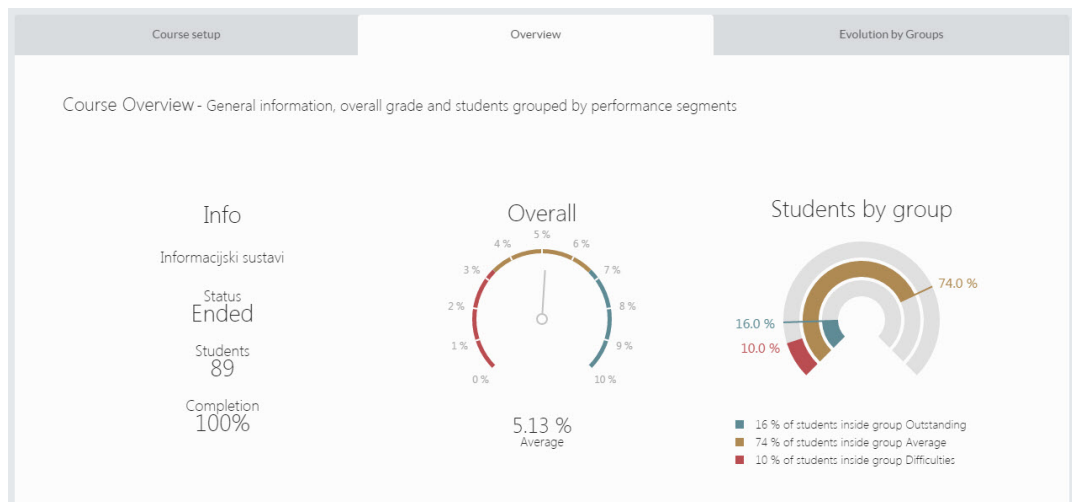


Figure 2.5.: Moodle SmartKlass Dashboard

2.5. Learner Dashboards

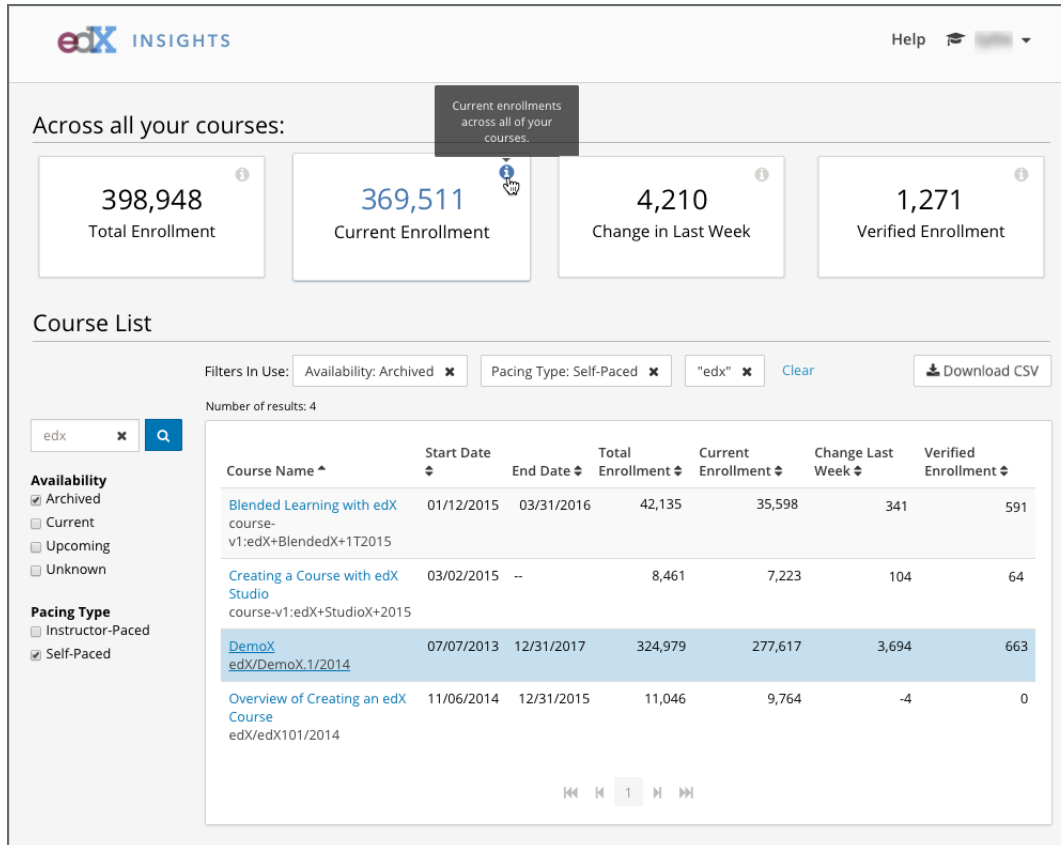


Figure 2.6.: edX Insights Course Instructor Sample Dashboard [16]

2. Background

As all these dashboards work with underlying data produced by students. For this so called personal data additional constraints such as collecting, storing, transferring it, apply. The increasing amount of data produced as by-product of online interactions brought along new perspectives on data privacy and ownership. This has recently found its legal manifestation in the General Data Protection Regulation¹⁶ (GDPR). Learning Analytics dashboards should not only fulfil the minimal requirements they were given by law or institutional agreements. The consequences of displayed metrics, calculated classifications created from personal data should be a core aspect and integrated from the early design phase on. The next section will briefly introduce one perspective on privacy and ethics for Learning Analytics.

¹⁶<https://ec.europa.eu/info/law/law-topic/data-protection.en>,
last accessed: February 11, 2019

2.6. Privacy and Ethics

With a shift in society considering data to be something valuable, discussions over ownership of personal data, the digital representation and virtual traces of one's behaviour increased. Individuals claim the "right to be forgotten"¹⁷ and decisions made by algorithms are publicly questioned over bias and validity. It seems that the entirety of consequences of producing and exploiting data are given more thought by the data's creators. Raising awareness by naming benefits and potential risks can be a starting point for further sound decisions, especially in the sensitive area involving learning data.

In this tensioning field of privacy versus Big Data, Learning Analytics, alongside other data science related fields, contributes to the discussion, by providing best practices, guidelines and good working examples. The vision of personalized improved learning should not act as a free pass on gathering data without limitations [23].

For the beneficial exploitation of Learning Analytics one needs to ask the inconvenient questions before applying algorithms and design tools so that they preserve data privacy. These are concerns and technically focused questions, but additionally remain open tasks and decisions upon general social aspects of information technology. These tasks can be addressed by agreeing on an ethical framework either on departmental or institutional level - or more abstract with a framework such as the one proposed by Greller, Drachsler [23].

When dealing with learner's data [2], questions arise such as:

- Who has access to personal data?
- How long is this data stored?
- What are the security measures for storage?
- Who owns the data?

¹⁷<https://gdpr-info.eu/issues/right-to-be-forgotten/>, last accessed: February 09, 2019

2. Background

Khalil et al. [36] sum up which challenges Learning Analytics have to face: Privacy, Security, Ownership, Accuracy and Transparency. The DELICATE framework (Greller, Drachsler) offers a starting point to discuss them [23].

The first question researchers have to ask then is why one wants to apply Learning Analytics. The added value of doing so and the rights of the data subjects are questioned. Openness about intentions and objectives are the second aspect that needs to be answered. A distinction which data shall be collected for which purpose is preceded by the need to define storage- and access rights. The legitimate access as institution or provider of MOOCs to collect additional data should be ensured. In general, involvement of all stakeholders and data subjects supports successful deployment of learning analytic tools. Upon that layer of integration, training and qualification of the staff interacting with these tools also needs to be considered. The framework suggests that consent should be acquired through clear and understandable questions. Furthermore, the technical aspects of guaranteeing privacy imply regular checks of security standards as well as updating access regulations. Eventually, when working with external providers, data security and usage should clearly be defined and all points mentioned before, should be applied.[23]

Such guidelines help to structure the process of applying Learning Analytics. Nevertheless there can be some hesitation due to privacy and its legal regulations. Despite the promises and chances with regards to Learning Analytics there seems to be a fear of unfair discrimination of data subjects. Some critics talk about the pressure to attune to the metrics Learning Analytics provide. Risks such as the loss of control over data traces are also associated with Learning Analytics. Outweighing risks and taking responsible actions by checking the above mentioned DELICATE framework is one possibility to mitigate the risks and compromise between benefits and drawbacks.

Taking this framework and lessons learned with regards to Learning Analytics with the LA Cockpit into account [37], [43], the WA Plugin and its design principles, features and limitations are discussed in the following chapter.

3. Web Analytics Plugin

The prototype implementation of the Learning Analytics Cockpit was finished at the end of 2017 and moved to evaluation and testing phase in an academic test environment the following year [42]. Designed as a plugin for the learning management system Moodle, the initial concept included requirements such as easy maintenance or modular and configurable system design.

The target user group were only administrators of the learning management system. The main focus was to show that Learning Analytics plugins can be deployed with open source resources and act as base source repository ready for quick and easy extension.

During the implementation and its time in the test environment the plugin acquired a list of feature requests by involved stakeholders. The considered future step for the LA Cockpit back then - making the plugin accessible for teachers on the MOOC platform - meant effectively enabling each teacher to use Learning Analytics for their provided courses. This outcome is revisited with the current fully integrated version of the LA Cockpit.

3.1. Foundation

Learning management systems gather basics statistics about the system and its status. Logging data about the content and the subjects interacting with the system is stored in so called "database log tables". The LA Cockpit first version used Moodle's system event table to group and aggregated daily metrics and coherences. These basic metrics have been encapsulated

3. Web Analytics Plugin

and visualized into so called "widgets". The MOOC administrator could add or delete these widgets and they were thought to not only showcase different visualization methods, but also act as a starting point for key figures the LA Cockpit is suited to aggregate data for. The metrics generally showed system-wide figures from within the learning management system. All these metrics have been adapted to the current version of the LA Cockpit, a basic overview of their definition and purpose is given here:

Logins over Time Figure 3.1 shows this metric where successful distinct logins into the platform are counted, aggregated daily and saved. A line chart shows data from the selected filtered date range.

Quiz Attempts Figure 3.2 shows the daily status aggregation of open quizzes. The states *finished* and *in process* are displayed for each active quiz.

Forum Posts per Forum Figure 3.3 shows the widget where activity in forums is grouped by the number of written posts. The number of users for each category (number of posts) is aggregated daily for courses, allowing a side-by-side comparison of course forums.

3.1. Foundation

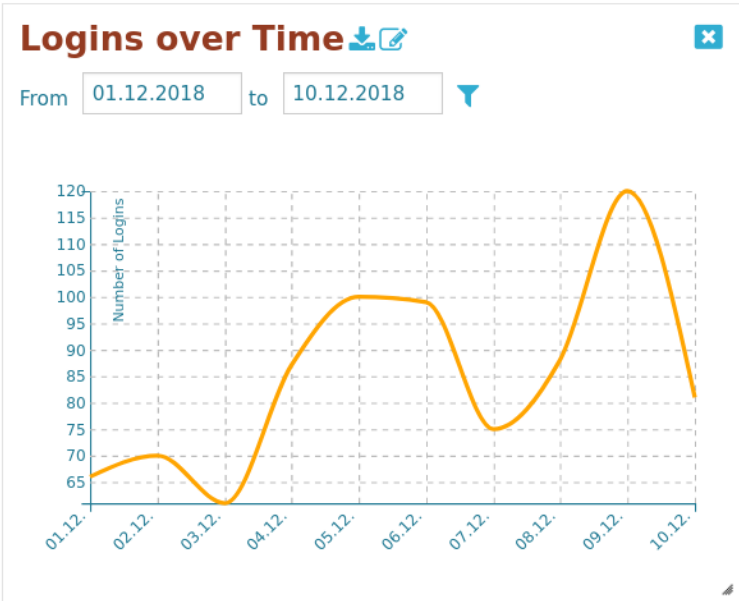


Figure 3.1.: Widget Logins over Time

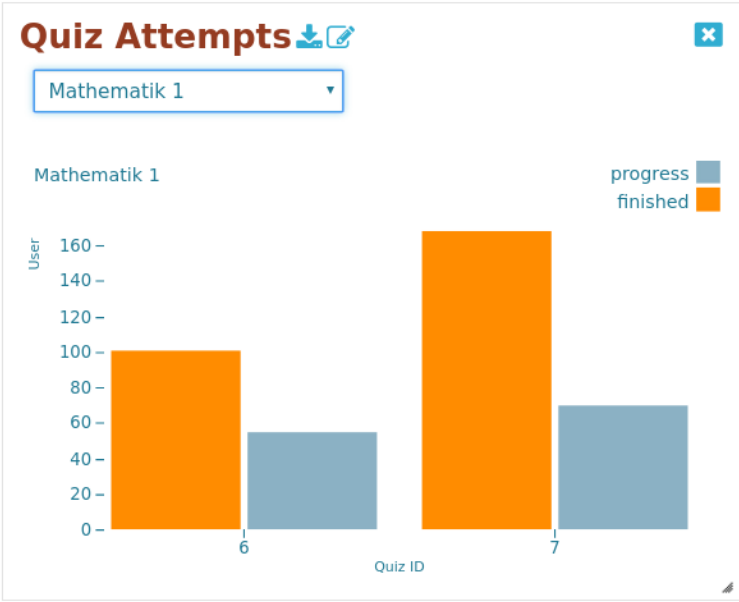


Figure 3.2.: Widget Quiz Attempts

3. Web Analytics Plugin

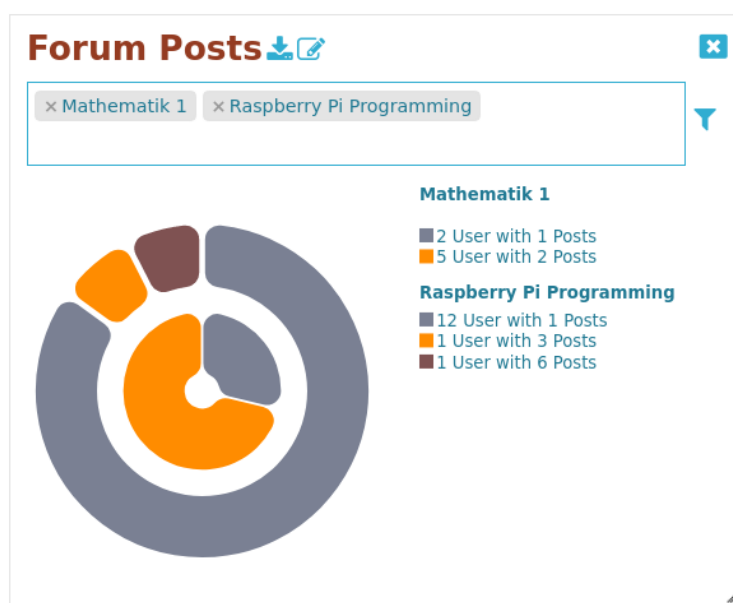


Figure 3.3.: Widget Forum Posts per Forum

Utilizing the cron job mechanisms provided by Moodle¹, daily aggregation from the log tables according to the metrics definitions are stored in separate database tables. The plugin holds its own database tables. For more detail upon the plugin's structure refer to the appendix A.2. The figure 3.4 shows a screenshot of the dashboard in its first version, whereas figure 3.5 shows the LA Cockpit and its widgets in the current version.

The LA Cockpit in its current version relies upon these existing daily aggregation mechanisms. Additionally it is improved with additional data traces from outside the learning management system. Capturing interaction within the learner's browser environment enriches the data available from within the LMS and provides new metrics and widgets. The next section will describe the basics of behavioural analysis and activity measurement. Further design changes, improvements of the LA Cockpit and the most prevalent addition, the new feature subsequently called Web Analytics (WA) plugin, are discussed within the next sections.

¹https://docs.moodle.org/31/en/Scheduled_task, last accessed: February 11, 2019

3.1. Foundation

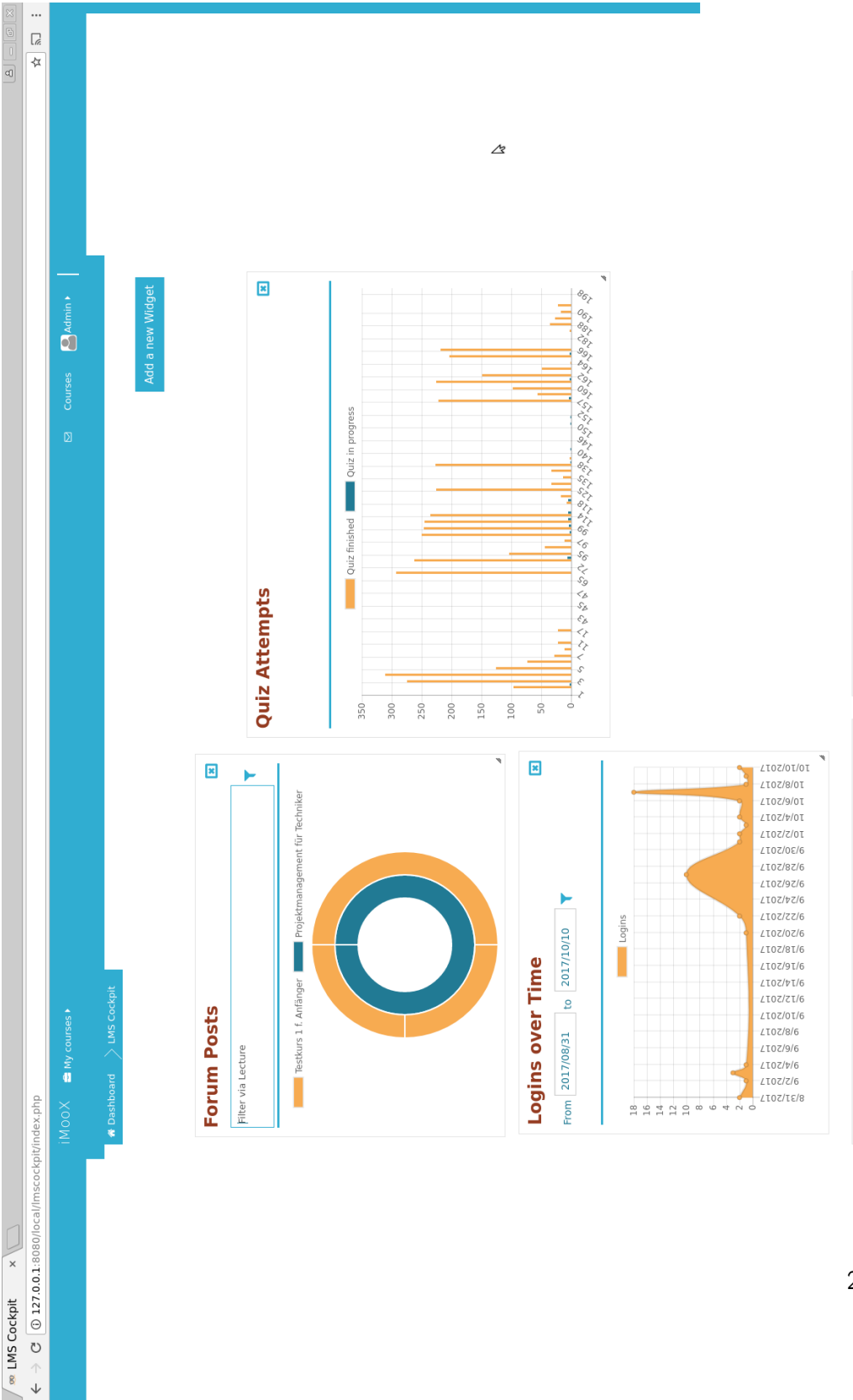


Figure 3.4.: LA Cockpit Dashboard First Version

3. Web Analytics Plugin



Figure 3.5.: LA Cockpit Dashboard Current Version

3.2. Activity Measurement

When designing learning analytic tools, one focus is on the content to be displayed. Which key figures should the tool to provide? Such questions relate to the first proposed step of the DELICATE framework [23]. The added value of a MOOC-centered Learning Analytics tool are insights into key figures. These would otherwise not be detectable due to the nature of the big datasets. New information and gained knowledge about the course, its content, the users and their interaction within can be provided by the LA Cockpit.

In the environment of many online learners distributed amongst various courses, the connection between teachers and learners is radically different to traditional face-to-face environments. Educators only receive feedback from the learner via their final grade or via explicitly requested responses. One needs to rely on the learning management system for additional, implicit feedback of the interaction process, but simple statistics of the system do not adequately mirror the learners' action within the content enough. The LA Cockpit should re-instantiate this cognitive connection between teachers and learners and enable teachers to use their pedagogic knowledge with the displayed information.

When defining the content to be displayed, this thesis uses metrics and widgets synonymously. As data source one can access the LMS resources in form of data base tables, logged events and records of technical processes such as download count. This is often not enough to capture the manifold ways of learning, so research [6], [53] tries to make use of additional information (or multi-modal data) such as speech, writing or non-verbal interaction (e.g. movements, gestures, facial expressions, gaze, biometrics, etc.) during real learning activities to enlarge the data traces to create metrics from. The internal state of the learning process is quantified by capturing its external representation of learning.

"Multi-modal" could also refer to a client-server model. Internal resources refer to everything contained within the LMS and the server, whereas external resources can be seen as data available on the client/browser side.

3. Web Analytics Plugin

This view is adapted for the LA Cockpit since the LMS Moodle as well as the platform iMooX are available online. In these environments the question for the interaction between user and the system on server- as well as on client-side arises.

The learning management system itself logs a number of timely datasets. The metric *Logins over time* visualizes such events, a login to the system represents a started web session. But this refers to a started browser session and one should not take this as equivalent to the start of a learning session. What if the content available is accessible without login? Then a distinct login does not uniquely determine the access and the user's interaction with the learning material. The most prevalent problem is that a *logged-in* state does not indicate that the user really consumed the provided content. Opening a tab in the browser and switching to another tab creates a login event and a session but does not indicate anything else. One can not infer a started learning sequence and the time of the session does not automatically correlate to the time spent learning within the online course. Even an automatic time out cannot indicate a non-consumed or end of learning session. There are many reasons why this could happen, from bad internet connection up to real-life distractions where the learner picks up the session later on.

Furthermore, the question of presence in online resources relates to the problem of opening a session, and actively consuming something else at the same time. There is no distinct easy measure to indicate to which percentage the user has consumed the resources, nor what the learning impact is.

Learning activity is not a linear, finite, static process easy determinable through single events sampled over time. There is active research which employs different models with assumptions to approximate the learning process such as the Learning Tracker [28]. Others try do model the process e.g. for detection of close submitters [49]. Even more complex indicators besides time consumed are proposed and evaluated as quantifiers of the learning process [47], [20].

3.3. Web Analytics

Behavioural analysis connected with the purpose to provide a personalized learning experience is a thoroughly researched area. Research on e.g. cognitive behaviour in MOOC discussion forums [57] gravitates more towards the educational data mining aspect of Learning Analytics research. Another approach is to focus on cultural behavioural differences explored by country and culture [48]. Behavioural analysis takes different learning theories into account and bases their impact on personalized recommendations or adaptable resources, intended for each individual's needs. This adjustment involves the step of comparing, modelling and classifying learners' behaviour, which, depending on the approach and considerations might contradict the wish for privacy or fair treatment from the individual data subject's view.

The LA Cockpit's focus is on aggregated metrics rather than individual, single and absolute values. The main goal is to create a context for teachers without classifications or complex predictive modelling. With the help of the Web Analytics Plugin the LA Cockpit hopes to visualize - not only quantify - activity within a course in an aggregated mirrored view from the user's perspective. Insights into what the learners are doing within a MOOC and what resources they are accessing can provide a starting point for further research.

In the next section the details of the behavioural analysis approach with the Web Analytics plugin are discussed. Basic technical background of the LA Cockpit and the building blocks of the technology within its environment are discussed in chapter 4.

3.3. Web Analytics

The LA Cockpit provides means of measuring, identifying and visualizing the behaviour of MOOC participants with an additional plugin built within this thesis. Applying Learning Analytics only with the resources from the Moodle system is not enough, especially in the context of MOOCs. In the face-to-face classroom situation, teachers can observe, infer and act upon the learner's behaviour. Do students struggle to find a certain resource?

3. Web Analytics Plugin

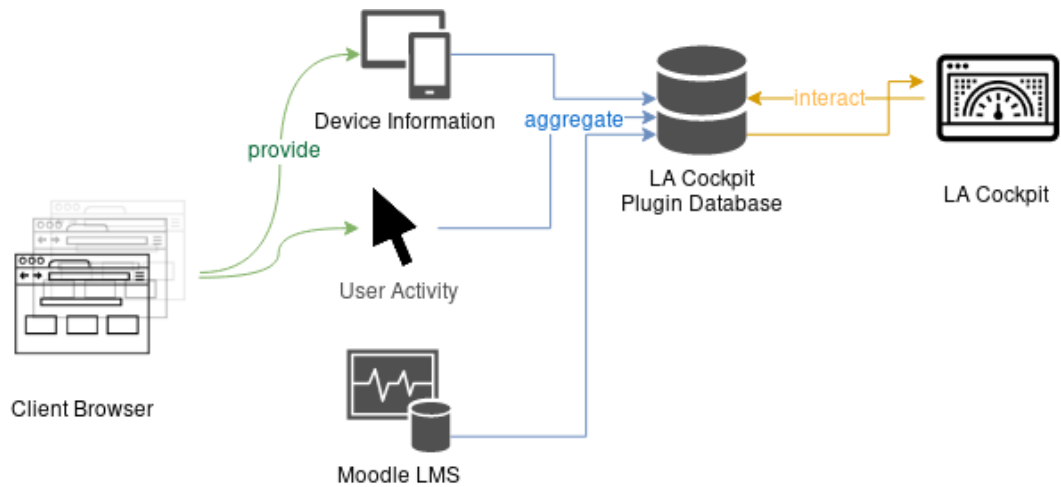


Figure 3.6.: Resource Interaction of the LA Cockpit

Do they need more time than expected? Do they answer their quizzes by going back and forth between video lectures and quiz questions? In the online environment of MOOCs the providing platform has no timely analysis capabilities of the interaction on the client side. Therefore the Web Analytics plugin tries to capture the interaction within the browser window, aggregating the interacting and offering an additional data source from the learner's perspective.

Figure 3.6 provides an overview of the involved resources. The aggregation of data does not happen user-wise, but resource-wise, from within the client browser. Within Moodle, multiple pages, distinguishable via their URL, represent one specific online learning course. Each URL is considered a single resource. This means, that for each accessed course page the activities of the learners are logged and daily aggregated into the LA Cockpit database. A more detailed technical description can be found in the next chapter.

Using the web browser to access the learning resources, interaction can happen via different types of input devices: mouse, keyboard, touch- or speech input, whereas mouse- and keyboard-interaction are considered standard input devices. With mobile devices, the mouse is replaced by

touch input, a physical keyboard is simulated with a virtual one. The way those input devices are used can relate to our cognitive processes and also depends on the presentation of the content.

From a technical point of view, behaviour can be categorized into different events happening within the system. These need to be interpreted by the browser to react accordingly, e.g. a click on a button opens a pop-up. The triggered event gets forwarded and processed by the browser, where the WA plugin aggregates different type of events. The following events are aggregated with their timestamp attached:

Mouse Movement Aggregation for changing x and y coordinates of the mouse pointer.

Click A click (pressing of a button followed by a release) event as well as a target resource upon which the event has happened (e.g. button, link).

Key Event Timestamp for the key event and if any special keys are pressed (Shift, Alt, Control).

Scroll Depth Scroll depth is saved within an regular interval. This refers to the calculated percentage of the page the users have scrolled to, where the top of the webpage is considered 0% and bottom of the page would be 100%.

The main data provider are mouse movements. A mouse movement can be defined as continuous event sampled at consecutive points in time with according x and y coordinates, creating a discrete data trace over time. All visually guided movements (e.g. selecting, pointing, clicking) are formed through gestures with the mouse device. In the WA plugin's database a mouse movement is described by consecutive logged entries, similar to the example in table 3.1. The database field *id* refers to a consecutive log number, *timestamp* is the unix timestamp of the triggered event, whereas *eventtime* is the JavaScript generated timestamp. The latter is calculated from zero, defined as the creation of the web document, on and is reset with a reload of the web document. The WA plugin saves both for redundancy reasons. The *courseid* directly relates the Moodle LMS to the course URL saved in *wl*. The position of the mouse event is given by its values *xpos* and *ypos*, calculated from the coordinate system where (zero, zero) starts

3. Web Analytics Plugin

at the top left corner of the web document. For the metrics, the number of database entries grouped by these coordinates are used to generate the heatmap value. For more technical details on the database structure refer to appendix A.2.

id	timestamp	eventtime	courseid	wl	xpos	ypos
42	1544973211085	1186	4	.../view.php?id=4	492	256
43	1544973211085	1188	4	.../view.php?id=4	498	261
44	1544973211087	1191	4	.../view.php?id=4	504	262

Table 3.1.: Example Log Entry of Mouse Movement

There are many different ways to use and consume web content, mouse movement analysis can provide the necessary data for the goal of the WA Plugin to identify overlapping regions of interest. Especially as this collected data results from real life situations and not from a controlled lab situation previous research results about correlation cannot directly be transferred. The next section discusses some limitations of the WA Plugin and explains the soundness of the data aggregation for their purpose within the newly created widgets of the LA Cockpit.

3.3.1. Limitations

Input devices are not only mice or keyboards, especially with portable computers or mobile phones one also needs to consider them as another option. Web applications can either directly process touch-based input by using touch events or the application accesses them as interpreted mouse events².

The WA plugin only aggregates mouse- and mouse-interpreted events, meaning that touch-only events are not or only partially aggregated. This depends on the various combinations of platforms and browsers and their versions and is a quite costly task to fully cover. One example of not fully

²https://developer.mozilla.org/en-US/docs/Web/API/Touch_events/Using_Touch_Events, last accessed: January 26, 2019

3.3. Web Analytics

registered events is the pinch-to-zoom gesture on some mobile phones. Multi-gestures like this are only partially registered with the first starting tap interpreted and registered as a mouse move. Part of the motion and its position relative to the content is captured, therefore it sufficiently contributes to the aggregation task of capturing behavioural data traces.

A second limitation relies to the sampling of the mouse events. The user interaction is happening continuously in real time, whereas each logged event is represented by a discrete timestamp. The data stream the tool produces has a sampling rate influenced by various factors. First of all, the input device itself. A mouse has a polling rate, measured in Hertz, and has some according polling interval. This defines how often the mouse reports its position to the computer, this usually occurs once every interval milliseconds of time. 125 Hz means that the mouse position will be sent every 8 milliseconds to the computer. In that context the term Dots per Inch (DPI) measures how sensitive the mouse is - the higher the value the farther the mouse will move on the screen for the same real life distance moved.

On top of this, discrete-valued representation of the mouse movement the event triggered within the web content, might add another layer of inaccuracy. The interception of the mouse event is done with JavaScript in the WA plugin, microsecond timings for events are theoretically technically achievable. To mitigate recent security threats such as Spectre [38], browsers currently round the result of queried timestamps to varying degrees. Some may slightly randomize the timestamp. Firefox³ or Chrome⁴ deploy different strategies, but this added noise of microseconds does not need to be further addressed in the context of the WA plugin. Assuming the whole data trace of a mouse move being sampled at a lower rate does not negatively influence the data aggregation nor the visualization of the behavioural analysis within the LA Cockpit.

³https://developer.mozilla.org/en-US/docs/Web/API/Performance/norow#Reduced_time_precision, last accessed: January 26, 2019

⁴<https://developers.google.com/web/updates/2018/02/meltdown-spectre>, last accessed: January 26, 2019

3. Web Analytics Plugin

A third limitation relates to the fact, that there are various correct ways of achieving the same goal (e.g. downloading a resource, accessing video lectures), each way depending on different cognitive processes and personal traits. One scenario could be that when browsing the webpage the user's mouse is an anchor, resting at the top of a paragraph to be read. Another user might highlight the passage read along the text, marking sections to be copied while reading further on the displayed content. Using keyboard shortcuts to flip through pages or scrolling down the web page would also leave the mouse at a position not correlating with the user's centre of visual attention.

"Several works in this area (mouse tracking, mouse movements, behaviour analysis) have provided evidence indicating that the mouse cursor can act as a weak proxy of gaze [3]", and offer an inexpensive alternative to eye tracking [26]. The strength of the correlation depends on the design of the website [9]. So it is important to notice, that mouse movement analysis are no suitable replacement for eye tracking studies. The equipment necessary for those studies is far more expensive and requires a predefined lab setting. These environment requirements are not transferable for the target application of the LA Cockpit. Nevertheless mouse activities provide a suitable data source for reviewing the design of webpages and assess the user activity within certain areas. For the WA Plugin these data traces are visualized within metrics in a way so insight to distant processes otherwise not observable is then possible.

One of the main goals of the WA Plugin is to provide insight into the MOOC communities' use of learning resources, and this can be provided by the plugin when making use of the aggregated data traces. To utilize these, one first needs to formulate metrics to provide reusable interpretation results. The ones decided to best represent such learners' activity are listed in the following section.

3.4. Metrics

The aggregated data from the WA plugin still needs some further refinement before becoming usable within widgets of the LA Cockpit. It might not be necessary or helpful to display all raw data in every detail. The target group should be presented with widgets easy to interpret and understand. Therefore meaningful subsets of the information have been agreed upon and the activity data will be represented with three new additional metrics:

- M1** Device Statistics
- M2** Activity Calendar
- M3** Heatmap

These should provide the teacher with a starting point for discussions on how students interact with learning resources. The web analytics feature offers researchers the chance to create further analytical features of the LA Cockpit related to this behavioural analysis data set. Each metric provides a different perspective on the aggregated interactions, the foundations of the metrics and its visualizations are explained below.

3.4.1. M1 Device Statistics

Reoccurring questions when providing online course content from the technical point of view are the following:

- Which operating system do visitors use?
- Which browser (version) is used?
- Which language settings are used?

The course content is presented within the learning management system. It features a responsive layout, so themes change and adjust depending on the device or resolution the user accesses the course with. Additionally, current content relies on state-of-the-art web technologies, such as embedded video content. The user group and their means of accessing the course may vary from course to course. Therefore, it might be of interest to provide a quick

3. Web Analytics Plugin

overview of the platform/browser distribution amongst the attendees to e.g. combat browser compatibility issues. Additionally preferred browser language settings let course instructors adjust to e.g. English resources or interpret misunderstandings in forum discussions under another light.

Therefore the widget *Device Statistics* consists of three categories, the language setting of the browser, the used browser and the used operating system. These three datasets have not been separated into three neighbouring charts. This would result in inefficient and overloaded visualization when comparing small charts and numbers next to each other. Still all three data sets are strongly linked, so filtering via radio buttons offers a quick context switch for one area of data visualization, displaying different information. In the legend, an absolute value indicating how many of the called site accesses contribute to each category is displayed.

The chosen visualization method is a doughnut chart and the filter option to switch between data sets with radio buttons. Figure 3.7 shows a screenshot with two of the three possible options checked, displaying values from test data.

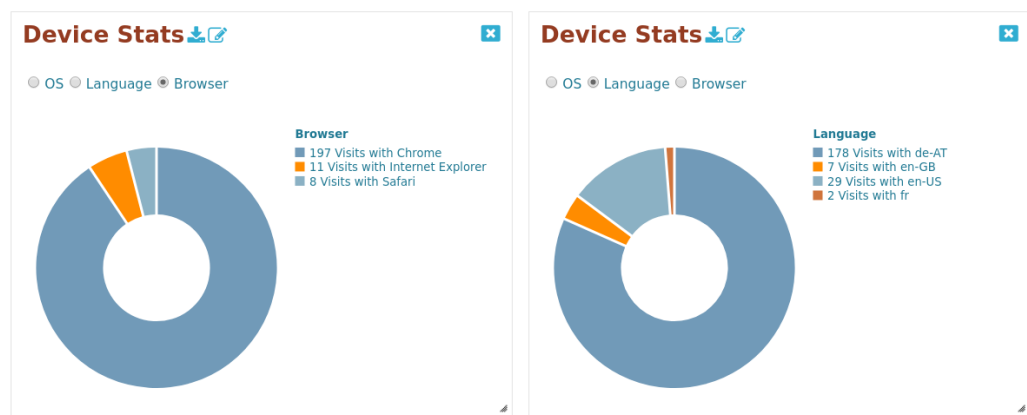


Figure 3.7.: Widget M1 Device Statistics

3.4.2. M2 Activity Calendar

Activity or Contribution varies over time, not only over a day, especially e.g. in the context of MOOCs over the timespan of the offered course. For self-paced courses which can be started at an arbitrary date, it is of interest to measure, document and visualize the efflux over the weeks or months for this steadily available learning content. Sometimes special events trigger additional course registrations, which can be noticed by more accesses within the learning management system. More interestingly, assuming a homogenous group of learners within a course, is the time when the users are online and consume the course content. Are certain weekdays more popular? Does more of the learning occur over the course of the day or are there increasing activity during the evening hours? Generally there might be repeating patterns not directly observable. This is the additional insight which this metric hopes to capture.

A calendar to keep track and visualize such events can prove helpful in identifying patterns. A very well known implementation is the so called Github contribution graph or contribution calendar⁵. In gradient colour scale the activity - for Github activity mean commits to the repository - are visualized. Lighter colour indicates less and darker shades more contributions to the repository.

The WA Plugin considers mouse events to be activities and add up all of those. This is done separately for each course on a daily basis. Although the WA plugin provides a larger set of activities to be aggregated (click events, keyboard interaction) the choice to only include mouse events for the metric stemmed from two assumptions. First, each click or keyboard interaction is preceded by at least a minor mouse event. Second, most of the interactive content involves this input device, making it the most used input device for web content. Therefore it is considered a suitable basis for an activity measurement in calendar view.

⁵<https://help.github.com/articles/viewing-contributions-on-your-profile/#contributions-calendar>, last accessed: January 20, 2019

3. Web Analytics Plugin

Figure 3.8 shows the widget *Activity Calendar* with a small test dataset with varying daily activity within the last displayed week. Hovering the squares representing one day each, interactive tooltips display the date and calculated values accordingly.

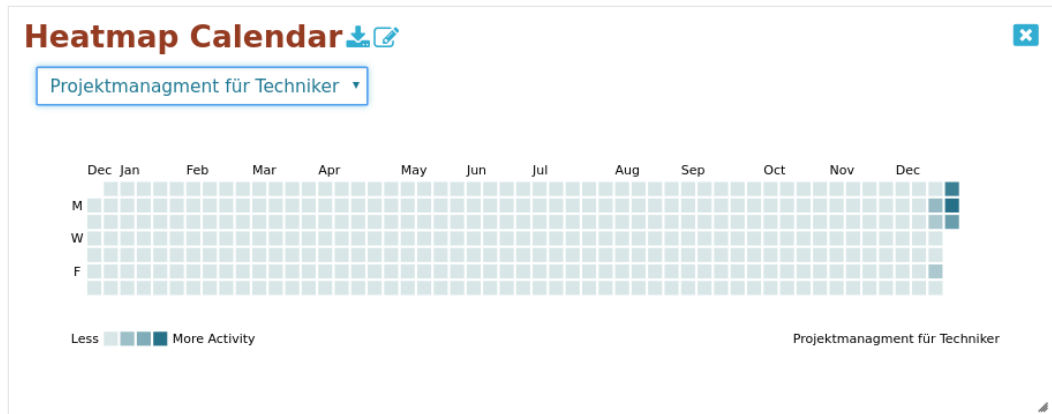


Figure 3.8.: Widget M2 Activity Calendar

3.4.3. M3 Heatmap

A well known tool of user experience evaluation are heatmaps. Heatmaps are generally defined as two-dimensional representation where values are represented by colours [22]. One common form are mouse- or eye-tracking heatmaps, taking x and y position from the displayed content, and a colour scale indicating how often the according position was accessed by the user through movement. There are many commercial software products available such as Matomo⁶, Hotjar⁷ or MouseFlow⁸ which provide a complete range of extensive tracking options and connected visualization services.

⁶<https://matomo.org/docs/heatmaps/>, last accessed: January 26, 2019

⁷<https://www.hotjar.com/>, last accessed: January 26, 2019

⁸<https://mouseflow.de/>, last accessed: January 26, 2019

3.4. Metrics

For the purpose of the LA Cockpit it is necessary to show how user interact with the course content. Are the important elements directly accessed? Additionally, with the aggregated mouse activity, one can infer how far down the page users have scrolled. For each course various generated heatmaps are available. Generally, for each page within the course (identified via the URL) multiple heatmaps will generated. Each combination of course URL and website resolution generates another map. Due to the responsive nature of the website design it is necessary to inspect them separately. For each page the WA plugin saves the displayed content as an image. This way, the aggregated data acts as an overlay and the coloured regions can be set into relation with the visual elements of the course page. The classic colour scheme ranges from red over yellow up to green. Red indicates areas that are accessed more frequently, where this could either result from more users accessing that area or spending more time on that region. Both contribute to a denser area in the heatmap, whereas less used areas are identifiable in yellowish or greenish tones.

The widget itself resizes the content of the heatmaps to the outer size of the widget on the LA Cockpit dashboard. The aspect ratio is kept, but some level of detail might be lost. Suitable as an overview and for selecting the desired URL resource, it allows the user to explore the original sized heatmap with a double click upon the widget. Scrolls bars make up for possible size differences between the space available on the users' display and the resolution of the heatmap. Figure 3.9 shows one of the generated heatmaps from test data, displayed within the widget. A screenshot of the full resolution heatmap and its integration within the dashboard can be found in figure 3.10.

3. Web Analytics Plugin

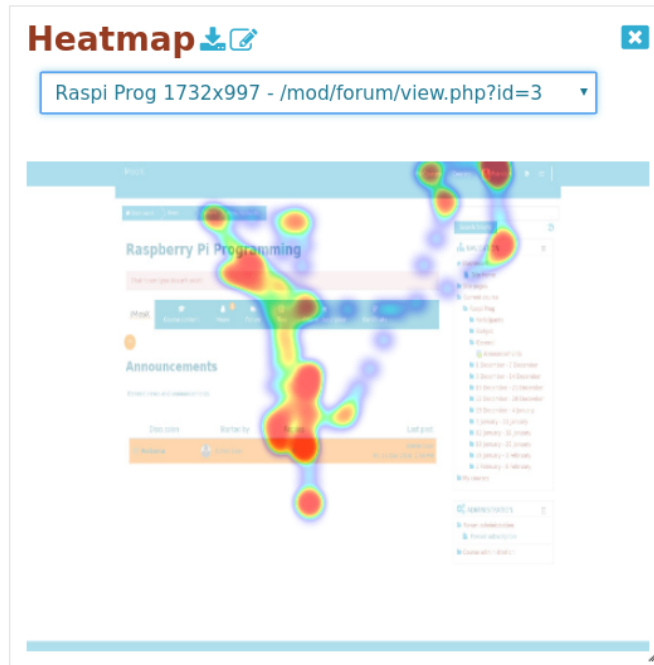


Figure 3.9.: Widget M3 Heatmap

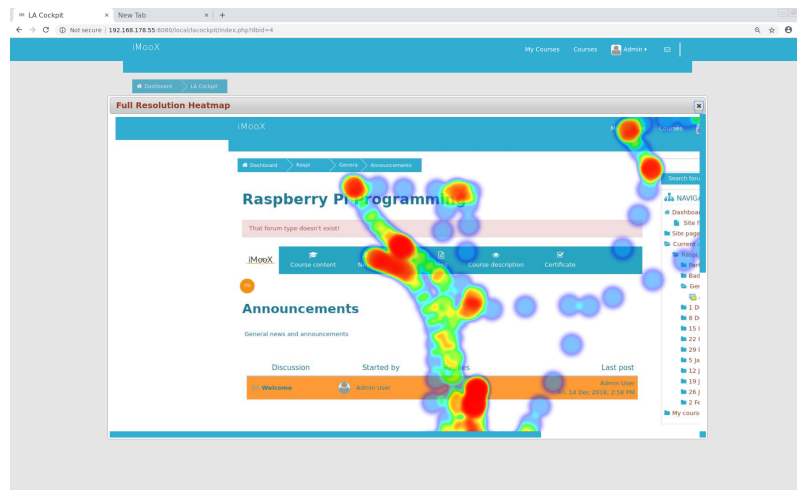


Figure 3.10.: Widget M3 Heatmap Full Resolution

3.5. Visualization

The visualization should convey all important key metrics without cluttering the display. Encapsulating the visualization as widgets seemed the most suitable choice. The user has full customization options of the dashboard within which widgets they add, where to place them or at what size they should have. At the current status of the LA Cockpit it was a deliberate choice to have unique widgets and disallow multiple widgets displaying the same metric. The framework can easily be adapted, but the type of visualization was carefully selected to best convey the underlying data and match the metric. Multiple varieties of the same metric might overwhelm the target user group.

Filter Options

Each widget follows the same design guidelines: consisting of basic control elements such as a close button it features three distinct areas:

Title Title of the widget and two icons, one for the export as picture, one for adding a note section to this particular widget (refer to Appendix for depiction, e.g. figure 3.12).

Filter Area If applicable, filter options are grouped here. That could be date pickers, radio buttons or search input boxes.

Visualization Area Area holding the chart, the visualization of the metric.

Interaction with the displayed data does not change the metric it was constructed from. There is no alteration in the original dataset of the database, but the filter options are stored by the LA Cockpit, so that upon the next login or reload of the dashboard, the last current state is restored and the according subset of data is displayed.

Default Selection

By default, some widgets do not display any data after initial creation. When adding it to a dashboard for the first time or re-adding it after

3. Web Analytics Plugin

deletion, the user is prompted with a notice in the visualization area stating that they first need to select a dataset from the filter options. Especially with e.g. the Heatmap widget lots of data needs to be loaded and a long list of options which set to display, is available.

This two-stepped process gives the additional benefit of nudging the user to interaction over efficiency in data processing. Additionally, if data grows over time it might be that it exceeds the space available on the widgets. The user can resize the widgets any time, but the clear structured default subset should improve the user satisfaction.

Labelling and Export

The LA Cockpit has to bridge two seemingly contradicting requirements. On the one hand, the widget's visualization should be as self-explanatory as possible, containing easy distinguishable colour schemes, labelled axes and legends. On the other hand, we want to keep a clean and simple dashboard and not overload the smaller visualization area. Keeping a simplified layout should animate the user to explore the visualizations themselves by hovering over parts or making use of the filter options.

There are various interactive visualization elements, most often tool-tips. Hovering over any data point provides additional information, including precise numbers or additional labels explaining which subsection is hovered.

A strong focus on explicit transfer of meaning of metrics is visible within the design of the LA Cockpit. This is achieved by two strategies: Extensive labelling and naming of chart elements. If one would solely rely on information hidden with tooltips, this interactivity gets lost when exporting the metrics. The second feature to support accurate Learning Analytics information is connected to the PDF export functionality. In subsection 3.6.5 the additional note taking feature is described and how it ties into the exported document.

3.6. Improvements

The prototype implementation of the plugin used `chart.js`⁹ for basic charting purposes and displayed the metrics as basic bar chart or pie chart. The researchers in touch with the prototype expressed the wish for the `D3.js` library. Technically not being a charting library, but a library able to manipulate SVG/HTML it can be used for plotting purposes, too. In section 4.4.1 the functionality and differences to common visualization libraries is discussed in more detail.

Furthermore, with `D3.js` there is a profound concept on interactive exploration of data connected. The trade-off is a high workload for the creator of the widgets, which would increase with multiple different visualization views. Nevertheless conveying data in a way animating the target user group to work with the tool, can result in building deeper insights and fuelling the feedback loop to improve the LA Cockpit itself.

3.6. Improvements

The use of Learning Analytics requires some level of understanding of the underlying concepts and metrics. We can not expect everyone to pick up the right interpretation without deliberate design choices. Users do not want/accept limitations in the functionality well, as long as there is a dedicated support team. Therefore a list of various feature requests from the prototype implementation were gathered, sorted and discussed. The most important requests from the stakeholders involved into the LA Cockpit were:

- Positioning of newly added widgets on the dashboard
- Multiple Dashboards
- PDF Export
- Improve visualization
- More Widgets

⁹<https://www.chartjs.org/>, last accessed: February 12, 2019

3. Web Analytics Plugin

These improvements concerned not only the widgets, but also made changes on the higher abstraction level of the plugin necessary. The main addition, a small menu (see section 3.6.1) is holding menu items with prominent functionality. It was necessary to enhance the LA Cockpit without cluttering the free space of the dashboard. In the following paragraphs improvements of the prototype implementation compared to this current version of the LA Cockpit are discussed.

3.6.1. Menu

As the first step before further additional functionality a menu bar at the top of the dashboard was integrated, each one grouped as menu item into a well-known intuitive user interface design. Figure 3.11 shows the menu bar. There are three main menu items, grouped on left, *Dashboard Settings*, *Add Widgets* and *PDF Export*.

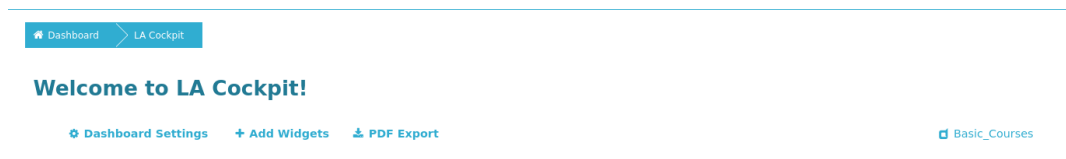


Figure 3.11.: Main Menu Element of LA Cockpit

Dashboard Settings Groups the new functionality from subsection 3.6.3. Hovering over or clicking it opens a submenu with the modal dialogue shown in figure 3.12.

Add Widgets Encapsulates the functionality from the button previously found in the upper right corner (see figure 3.4). A modal dialogue displays checkbox options to add the individual widgets not already displayed on the current dashboard.

PDF Export Provides the functionality discussed in subsection 3.6.4. Clicking the item automatically generates a document and downloads it to the user's local storage device.

3.6. Improvements

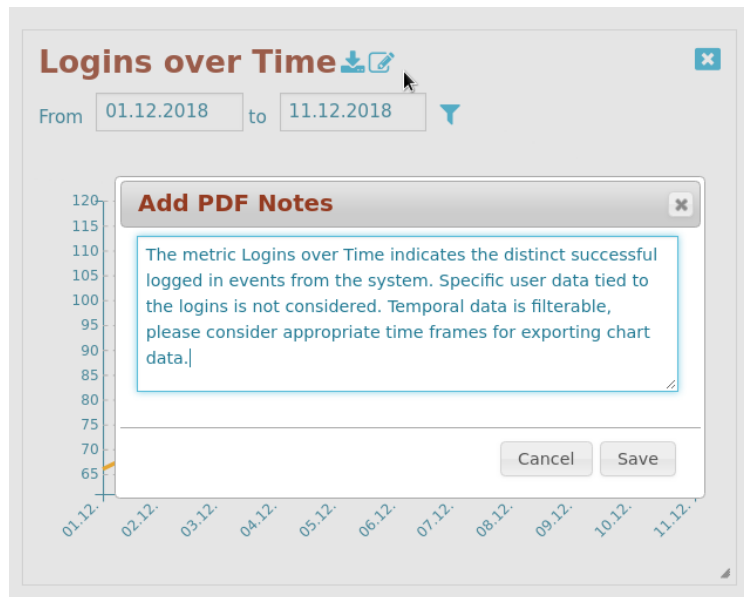


Figure 3.12.: Modal Dialogue for PDF Notes of Widgets

At the far right of the menu panel the name of the created dashboard is displayed as an visual anchor for the user. It updates when a new dashboard is loaded.

3.6.2. Positioning

In the prototype adding multiple widgets (up to three at that time) created all widgets at once on the same x and y position. This resulted in overlapping widgets. The user had to drag each item onto the desired position to be visible and accessible. Due to the highly customizable interface and the possibility to freely arrange widgets this was thought to be an intuitive process. Users did not realize that widgets were layered over each other and filed an error report, thinking that the other selected widgets had not been added. The LA Cockpit now creates any new widgets with its y position below the widget positioned at the current bottom. The theme on imoox.at features a footer, so adjustment of the dashboard size is needed.

3. Web Analytics Plugin

With this change and the prolonged scroll bar for the dashboard area the LA Cockpit gives their users a clear visual feedback of a successful modification of elements on the dashboard.

3.6.3. Multiple Dashboards

This feature is a direct consequence of trying to make the LA Cockpit accessible to a broader user base and supply every teacher with their individually customizable Learning Analytics tool. For the prototype the administrators shared one dashboard of the LA Cockpit. Now, with the ability to create multiple dashboards, course specific details, filtered datasets or completely different subsets of widgets can be grouped into separate dashboards and saved for later use.

The standard interaction with saved objects such as name, select, reload or delete adds upon the autosave functionality of the dashboard prototype (each modified widget saves its current position to the database after the dragging or resizing operation finished).

3.6.4. PDF Export

Despite being a web accessible tool sometimes it is necessary to pass on information outside of the context of the application. Providing third parties a report or having an offline documentation to themselves was a requested feature. This use case required the LA Cockpit to provide some sort of offline export functionality. Being freely arrangeable in order, dimensions and position, the dashboard restricts to no layout and is highly customizable. However, the exported format was decided to be of a stricter pre-defined layout. The menu icon exports a PDF file, consisting of a cover page (with at least title and date) and one page per visible widget from the current dashboard, see Appendix B.1 where an exported document is included for reference.

3.6.5. Notes

New users to the LA Cockpit might not be familiar with the concepts of Learning Analytics and how to interpret them correctly. To improve the transparency, why these metrics have been chosen, why they are visualized the way they are and what the caveats are for some specific underlying data set, the notes feature has been added. Each widget on a page is enriched with a note section. A little icon next to the widget's title opens a modal dialogue. This note section can have two types of content: either some default text, giving additional information regarding the displayed metric or it is already modified by the target user. With this, the LA Cockpit provides the space for any remarks, observations of outliers in the data or thoughts, directly where they relate to that widget. The notes are not visible on the dashboard and can be accessed via the modal dialogue to show, but to the generated PDF file, they are an integral part of the generated report.

4. Implementation Details

As part of the Moodle LMS the LA Cockpit uses the provided modules of current web technologies as well as further additional libraries.

The plugin itself is implemented in PHP¹, the server-side scripting language Moodle is written in. PHP is used to generate the plugin's documents displayed in the browser and in conjunction with SQL for the data aggregation.

The basics for the tool are Hypertext Markup Language² (HTML), the standard markup language for structuring and presenting content like webpages or web applications on the World Wide Web (WWW). Together with Cascading Style Sheets³ (CSS) to style the representation of said HTML documents the basic page and widget containers are represented.

With its current major version of the HTML standard, HTML5, provided an innovation with the canvas element⁴. The LA Cockpit prototype used the canvas element for holding the visualization for each widget's metric. The current version uses scalable vector graphics, SVG⁵ for that. JavaScript, another scripting language and third cornerstone of the WWW, the content can be modified in layout, look and behaviour for fluid client-side-driven interactive representations. The element itself has no drawing ability, meaning together with JavaScript graphics can be generated on the fly.

¹<https://secure.php.net/>, last accessed: January 24, 2019

²<https://www.w3.org/html/>, last accessed: January 24, 2019

³<https://www.w3.org/Style/CSS>, last accessed: January 3, 2019

⁴<https://www.w3.org/TR/html5/scripting-1.html#the-canvas-element>, last accessed: January 26, 2019

⁵<https://www.w3.org/TR/SVG11/>, last accessed: January 26, 2019

4. Implementation Details

Between server and client (and the client's browser) the Hypertext Transfer Protocol (HTTP) is the main application protocol, and it is used for transfer and display of various web content (which in the case of the LA Cockpit are HTML documents) in the WWW. Additionally, Asynchronous JavaScript and XML (AJAX)⁶ is the web technology that extends HTTP. It allows for more interactivity and enables webpages to update its content without HTTP reload. This is possible because instead of asking for new information, the client can do the data fetching itself, in the background. This is state-of-the-art in seamless interaction with web content.

4.1. Architecture

The prototype was designed as a plugin for the Learning Management System Moodle 3.1., being implemented as *local plugin* because this type features the most freedom for developers as it imposes no restrictions on structure, used technologies, design or capabilities.

The Web Activity plugin was realized as *block plugin* due to the easier integration of related JavaScript functionality within the course layout of Moodle.

Structurally, both plugins are folder structures in the source folder tree of the Moodle LMS, containing PHP scripts (and CSS and JavaScript). The Moodle core communicates with the plugin via particular pre-defined entry points, defined in files such as `lib.php` within the plugin (which therefore must be present).

The prototype implementation consisted of three main components, described in the bachelor thesis [42], two of them have been reused and adapted, namely the data aggregation and the metrics.

The visualization as the third component is revised to a different technology. In this section we will discuss the technology already used in the LA

⁶<https://developer.mozilla.org/en-US/docs/Web/Guide/AJAX>,
last accessed: January 28, 2019

Cockpit and any changes and improvements. The Web Activity plugin which provides new metrics related to behavioural analysis needs more integration points outside of the learning management system, all involved tools necessary are explained in the paragraph with figure 4.1.

4.2. Class Structure

An abstract factory design pattern allows efficient creation of widgets, whilst guaranteeing common functionality in the abstract functions and different concrete implementations. Future developers shall benefit when creating new widgets and metrics, not spending too much time on the framework itself adding new widgets to the LA Cockpit. All widgets available on the current dashboard are saved and subsequently queried from the database, then the factory is called on each and creates the corresponding widget. The corresponding database table can be found in Appendix table A.2.

The next section briefly discusses how interaction on the dashboard is handled from the technological point of view.

4.3. Dynamic Dashboard Interaction

After click on the LA Cockpit menu in the Moodle LMS, there are two possible scenarios: First, the last used dashboard from the user gets reloaded. All filter options and chosen widgets get restored and the current data gets fetched. There is no need for a separate updating step. If it is the first call of the LA Cockpit and the user did not create a dashboard so far, a new blank dashboard gets created, letting the user start from scratch, adding widgets to their liking.

For this interaction between the client's browser and the server side database information, AJAX requests are sent. Moodle requires those to be

4. Implementation Details

defined in `externallib.php`, where all calls between client and server, e.g. for fetching chart data or saving current positions, have to be defined.

4.4. Visualization

The LA Cockpit encapsulates each metric into a visual element called widget. They all share a common structure already described in section 3.5. The first prototype of the LA Cockpit used `chart.js` as visualization library. This was for basic charting sufficient enough, providing users with bar charts or line charts. The section discussed the improvements by switching to `D3.js`⁷ as visualization tool. The next section will shortly describe how this framework differs from the previously used one.

4.4.1. D3.js

The focus of the LA Cockpit of interactive visualization of big datasets from e.g. aggregated behavioural data made the upgrade to a framework handling complex datasets necessary. `D3.js` stands for Data Driven Documents and is a JavaScript library which focuses on state-of-the-art web technologies like HTML5, SVG, CSS and provides capabilities to manipulate these Document-Object-Model (DOM) Objects within a data driven approach. It is a successor to `Protovis`⁸, a graphical toolkit for visualization. `D3` is considered fast and supports large datasets and dynamic behaviours for interaction and animation in the visualization and it is supported by most major modern web browsers.

⁷<https://d3js.org/>, last accessed: January 27, 2019

⁸<https://mbostock.github.io/protovis/>, last accessed: January 29, 2019

In the first published article about the framework [7] the creators mention the trade-offs which come with using the library, where deeper knowledge of the underlying DOM Model are required to fully use the strengths of the flexibility despite the higher programming expense. A few notable differences to other visualization libraries are discussed in the following paragraphs, a more extensive overview can be found on the D3 homepage itself. A caveat is the versioning of D3, it has undergone major changes between version 3 and the latest version 5. For the LA Cockpit the latest stable version, version 5, is used.

Dynamic Properties

Another term one comes across when using D3 as visualization tool, is *binding data*. This refers to the concept of passing data (in various form, as array, json encoded or read from an csv) and being able to use this data for specifying colors according to the dimension of the bound data, without the need to rebind data, if the underlying array changes in size, if new additional values are passed to the function.

Especially this dynamic approach, fitting the representation to the data available rather than the other way round, lead to a concept new developer need to understand when trying to harness the full visual effects of interactive D3 visualizations. All elements are subject to states⁹, namely *Enter*, *Update* and *Exit*. Data points joined on existing elements produce an update. Unbound Data (new data) produce the enter selection, meaning missing elements in the current bound data. Similarly, all elements not referred to any more are part of the exit selection and mean these elements will be removed.

Understanding this concept is crucial when making dynamic visualizations. This defines so called transitions with fade-in effects and like and build the basic block of interactive exploration and animation. This concept also makes it easy to handle real-time data without extensive effort of calling redraw in a time frame. Allowing users to zoom into datasets and explore

⁹<https://bost.ocks.org/mike/join/>, last accessed: January 28, 2019

4. Implementation Details

the visualization themselves without delay enhances the user satisfaction and experience.

Despite the extensive options D3 provides, it comes with the trade-off of increased development time and rather extensive source code in terms of line count. Every element in a visualization needs to be handled by the programmer which results in a somewhat higher effort creating basic charts. As soon as transformations and animations come into play, this initial higher effort gets its return on investment.

4.5. Device Statistics

In the evolution of the web, the internet started off with a text-based system, where users navigated it by typing commands. Nowadays browsers do that work, when accessing resources, the browser is the "agent", turning the action into commands. When loading resources, the browser on the client side identifies itself to the server (it wants to access the resource from), with the User-Agent string.

In HTTP, the User-Agent string is used for content negotiation. The format is a list of product tokens/keywords, where the most important one is listed first.

One example token:

```
Mozilla/5.0 (X11; Linux x86_64; rv:63.0) Gecko/20100101  
Firefox/63.0
```

The language is defined in RFC 7231, section 5.3.5: Accept-Language¹⁰. This request HTTP header discloses which languages the client is able to understand and the preferred one, which reflects the language set in the browser user interface.

¹⁰<https://tools.ietf.org/html/rfc7231>, last accessed: January 26, 2019

For the WA Plugin this information is used within the *Device Statistics* widget. The browser user agent string is saved upon first access of the course URL to the LA Cockpit database. Upon widget creation, the server parses all available datasets and returns accordingly sorted subsets to the dashboard for visualization.

4.6. Activity Calendar

For this widget, a basic aggregation of mouse events is done, as explained in section 3.4. The count value of activities for each day is directly calculated from the data traces in the database. This is done on a course-wide level, where the maximum value within the courses are set as minimum and maximum and the other shades are derived linearly in between. All available events are binned belonging to distinct days, as the calendar provides a daily overview. The yearly view is calculated from the current date, providing a full overview of previous activities within the last twelve months. The metric is aggregated on the server side after the AJAX request, which is sent after selecting a course to display the data from.

4.7. Heatmap

The Heatmap widget consists of two main parts with different data sources. The activity data itself - visualized as traces between red and green - are aggregated from the WA plugin by analysis of the mouse activity of users. Without the displayed course URL these mouse traces would be hard to interpret. There is a strong visual link between the displayed elements and the traces. Therefore it is necessary to provide the layer of information the user has been presented. The background image of the widget puts the acquired data into perspective, for that an elaborate process creates these screenshots. Subsequently the widget itself presents only the list of URLs where background images are available to the target user.

4. Implementation Details

Technical prerequisites for the widget to work are: installed application of chrome headless, node.js application Puppeteer¹¹, test/demo user with access to the platform. Limitations to the screenshot process itself are user's individual resources (messages, private pages) not accessible to the test/demo user.

The daily aggregation of data from the WA plugin results in a list of course URLs accessed by the users. For all unique combinations of course URLs and screen size resolutions heatmaps will be available and screenshots need to be generated. A scheduled task (Moodle's cron job) will handle this screenshot functionality. Figure 4.1 describes the connection between all tools and processes used for creating those. The cron job queries the LA Cockpit database for the list of URLs to be processed. The cron job itself is a PHP file, and with the ability to execute system other applications outside of the Moodle instance can be called. In the case of the LA Cockpit a headless version of chrome¹² (headless means no graphical interface) is used to create screenshots. The process requires the browser open the window with the given screen size resolution, to navigate to the URL, possibly logging in to the platform. This behaviour of the browser is easier handled when wrapped into Puppeteer, the server side node.js application. This high level API can control the headless chrome instance and makes generating screenshots easier.

The browser creates the screenshots and places them in a temporary file. When the list of URLs is processed, the Moodle cron job picks up execution where system branched off and creates files within the Moodle System from this temporary file.

This is necessary because the created images should be served from the file storage of Moodle to the client as background image of the heatmaps. Moodle has a strict defined interface for that, the Files API¹³.

¹¹<https://developers.google.com/web/tools/puppeteer/>,
last accessed: January 28, 2019

¹²<https://developers.google.com/web/updates/2017/04/headless-chrome>,
last accessed: January 28, 2019

¹³https://docs.moodle.org/dev/File_API#Serving_files_to_users,
last accessed: January 29, 2019

4.7. Heatmap

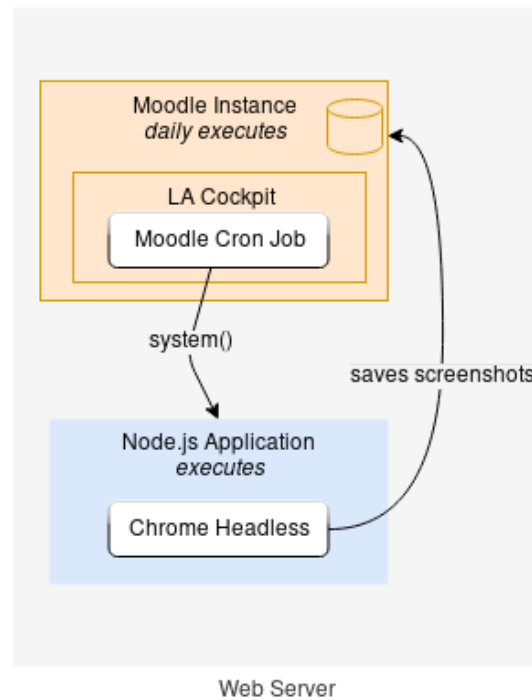


Figure 4.1.: Architecture of Heatmap Screenshot Aggregation

The node.js application source code called from within the Moodle cron job is listed in appendix A.3. The call expects environment variables for login (user and password of a demo user) to the platform and further parameters defining URL, width and height from the screen size resolution.

For the screenshot itself, there is no further processing needed after the execution. All screenshots are present within the data storage of the LA Cockpit. The Heatmap Widget uses the file serving capabilities provided by Moodle to fetch and display the images in the client's dashboard view.

5. Discussion

To provide a proof-of-concept for the LA Cockpit it was not only implemented or put into a test environment. Designed for the Austrian MOOC platform imoox.at it was tested within the productive system and was used during the course "LawBusters – Drei Themen Recht.humorvoll"¹. This MOOC started on 17th of December 2018 and featured 3 weeks of video lectures. The goal of this course is to convey law related basics in an entertaining humorous way, bridging law related facts with analogies from Science-Fiction and Fantasy.

The findings for the LA Cockpit and the WA plugin within this period (up to February 2019) from more than 60 learners are discussed in the following section.

5.1. Use Cases

The following use cases have been defined as basic and elementary for the LA Cockpit. They mirror typical interactions, challenges and needs of the users of the tool. The following main two target user groups have been identified for the current version:

Target User Administrators and Researchers

Target User Course Lecturers

¹<https://imoox.at/mooc/local/courseintro/views/startpage.php?id=55>,
last accessed: January 28, 2019

5. Discussion

Next, an excerpt of use cases is given, with the idea to define what the target users are trying to accomplish with the LA Cockpit on a functional level. Main tasks are represented and the settings they need to create, change or examine are listed as part of the use cases.

Initial Login

Precondition: access rights to LA Cockpit

1. The user logs into the Moodle System.
2. In the navigation tree the menu point LA Cockpit is chosen, a click upon it refers to the dashboard.
3. The last modified dashboard of the user is reload. A blank one is created if the user logs in for the first time.
4. All widgets update to the data available in the database.

Adding of Widgets

Precondition: logged-in user, dashboard available

1. The user chooses the menu point Add Widgets.
2. The presented list matches all available widgets not yet displayed on the dashboard.
3. The user selects a widget to add.
4. The modal dialogue closes, a page reload adds the new widget on the bottom of the dashboard.
5. Data is loaded or the user is prompted to select what to fetch data for, first.

Adding notes

Precondition: logged-in user, dashboard available

1. Any widget is chosen to be attributed with information.

2. The user clicks on the icon for the note section next to the title.
3. In the modal dialogue the default information about the metric is displayed.
4. The user adds their own observing related to this metric.
5. After saving and opening the modal dialogue again, the user's modification are there.
6. Alternatively, the PDF export shows the modified note section.

PDF Export

Precondition: logged-in user, dashboard available, at least one widget on dashboard

1. The user chooses the menu point PDF Export.
2. LA Cockpit generates and download a PDF to local storage.
3. When opened, the generated file has a cover page, and each widget is exported on an individual page, including its note section modified in use case *Adding notes*.

Filtering Logins over Time

Prerequisites: logged-in user, Logins over Time Widget available on the dashboard

1. The user filters data based on a time frame different to the currently displayed one with the date picker.
2. Upon click of the filter icon, the datasets animates the corresponding subset of data and adjust the labels and content itself.
3. Upon a reload of the dashboard, the last options are reloaded and the filtered dataset is displayed.

The use cases for applying the filter options for the other widges have been omitted for redundancy reasons.

5. Discussion

Creation of New Dashboard

Precondition: logged-in user

1. The user clicks on the menu point Dashboard Settings.
2. The sub menu item Create New Dashboard is chosen.
3. In the modal dialogue the user chooses a name for the new dashboard.
4. Upon saving, the LA Cockpit reloads and displays a new, blank dashboard without any widgets.
5. The info on the right of the menu displays the chosen name.

Reload of Dashboard

Precondition: logged-in user, at least one saved dashboard

1. The user clicks on the menu button Dashboard Settings.
2. The sub menu item Load Dashboard is chosen, a modal dialogue opens.
3. The user selects a dashboard to reload from the presented list of available items.
4. Upon select a reload occurs and the current dashboard and its widgets are replaced
5. Data is loaded or the user is prompted to select what to fetch data for, first.

5.2. Privacy

Behavioural analysis of users on the internet is nothing new and often has the negative touch of tracking, surveillance and if happening without consent, is ethically questionable. The process is similar to clickstream² analysis. Most often found for marketing purposes, the user's interaction (with web content) is tracked in every detail. There the whole path of the user interaction and its environment is recorded and can be accessed by the individual's identifier. These would allow a replay of the whole action on the respective website. For the goal of the WA Plugin, to provide analysis of the interaction with presented content as a whole, this tracking of individual's performance would not be justifiable. Learning processes can be seen as sensitive data and there is no expected benefit for the LA Cockpit in user profiling when distinguishing between individuals and their means of learning.

The DELICATE framework [14] offered guidelines how to handle the need for aggregated data in unison with the individual's rights and interest. For the small subset of test data of the WA Plugin clear consent is asked for research purposes with the login to the platform. Additionally, the plugin does not separate individual user's action. Re-identification or personal behaviour were not the goal of the WA plugin. The metrics created are on a course- or course-page wide level for the whole group of participants.

5.3. General Feedback

Since its first enrolment possibility in December 2018, nearly 90 students have registered themselves for the "LawBusters" MOOC. An initial third of these participants started the course within the initial time frame December to January. The following weeks, up until February 2019, a steady intake of learners can be observed. The course has no defined end date and is

²<https://dictionary.cambridge.org/dictionary/english/clickstream>,
last accessed: January 26, 2019

5. Discussion

still open on the iMooX platform, so further students can be expected to join and complete the online course.

Featuring a course format of three distinct video lectures, spanning over three weeks, participants can expect colleagues to be available for discussion and exchange on presented interactive forum tasks. The LA Cockpit with its addition, the WA Plugin, were integrated on the MOOC platform with the initial start date of the LawBusters MOOC, figure 5.1 shows a screenshot of an created dashboard from the course data in February 2019.

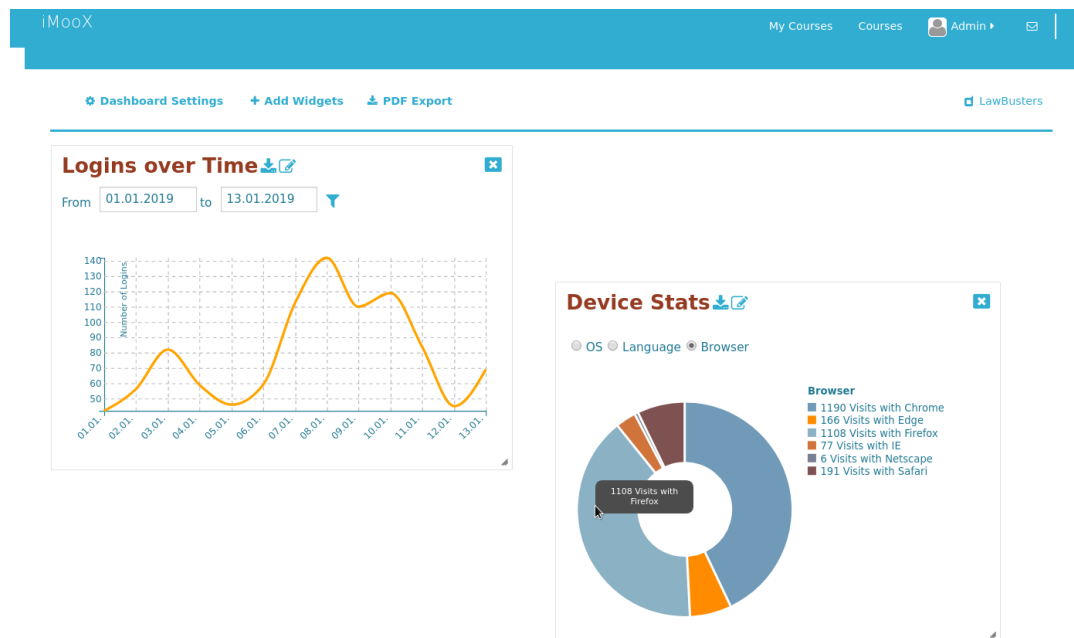


Figure 5.1.: LA Cockpit Law Busters Dashboard

Multiple Dashboards

The general feedback on the LA Cockpit shows that the main goals from section 5.1 can easily be achieved. Exemplary is the feature of the multiple dashboards. The basic concept proved beneficial in grouping different

widgets to different likings of the target user, e.g. course-wise. Nevertheless when administering a larger set of courses, having only the name as a distinction of the created dashboards might not be enough. Further details such as creation date can help to find the desired item in a list faster and improve satisfaction with the tool.

PDF Report and Export Functionality

Similarly, the export of the PDF Report was happily accepted. Having hard copy reports available caters to some educators, preferring paper over pure digital reports. Furthermore, sharing common findings or metrics from course-related information is enabled via report creation of a dashboard or export of single visualizations. Such smaller pieces of information can be shared without elaborate access and authorization process to the LA Cockpit and the Moodle platform. Minimizing administration overhead and simplifying sharing of results is commendable in the eyes of the target user groups.

The pre-defined naming scheme of the generated report file is fixed at the moment, but could be up to the decision of the target users, together with a free choice of the location where to save it to.

Note Section

The note section for widgets received broad reception. It is considered to improve understanding, especially of users new to Learning Analytics. The willingness to apply Learning Analytics is encouraged and the feature to document own observations and findings proved helpful. Users adapt it even for the basic task of reminders related to the displayed metrics. Referring to the LawBusters MOOC, the Christmas holidays in Austria left a distinct decline in logins to the MOOC platform, as visible in figure 5.2. Such general remarks can find their place in the note section and act as a documentation for later comparisons of displayed data.

5. Discussion

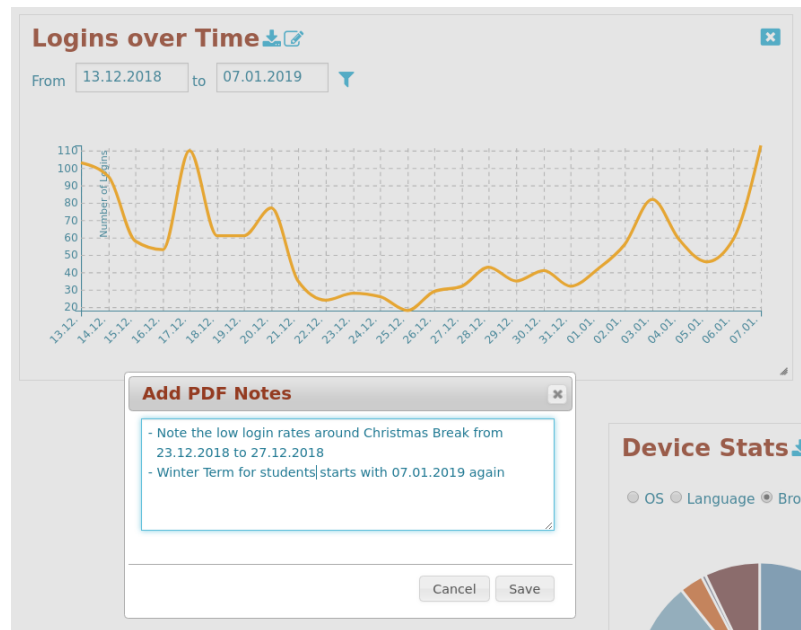


Figure 5.2.: LA Cockpit Law Busters Login Widget Notes

Metrics

The behavioural analysis with the WA plugin aggregates a wide stock of data. Only a subset of those are currently visualized in Metrics M1 to M3 from this thesis. Further details about the users experience with the course can be visualized and have been suggested from the target user group of researchers and administrators. A contribution of how often the keyboard is used within the forum context could give hints about the usage of search bars to access learning materials. Flow diagrams where most clicked resources are listed could provide an insight of the order content is used.

Regarding the provided metrics, insights to underlying data from the Law Busters MOOC and what is considered helpful by the target user group is discussed in more detail in section 5.4 Widget Feedback.

Design and User Experience

Additional prompts are realized by opening up modal dialogues, providing input fields while disabling interaction with the currently not active content in the background. This was noted by some people to hinder their workflow, they expected to have all interaction possibilities available at all times. The dragging and resizing of widgets is naturally adapted and especially helpful during the setup phase of a new dashboard. It was seen that after initial creation, the interaction with the dimension or order of the widgets reduces.

Animation and Transitions when filtering data are a general positive remark concerning the widgets. It improves user satisfaction and chance to come back to the dashboard for visualizing new datasets.

The current color schemes used for visualization are chosen to maximize discrimination and disambiguation, especially with items taking up less visual space or grouped next to each other. With regards to the PDF Export, these colour choices could be re-evaluated and improved for user experience. At the moment there is no focus on accessibility, for instance, considering users with dyschromatopsia.

5.4. Widget Feedback

The structure of the widgets and its displayed metrics have been described in previous work [42] and in section 3.4. The widgets discussed here were chosen to be applicable for the test period of the Law Busters MOOC and grouped on the dashboard (figure 5.1) to be inspected by administrators. The findings and insights provided from the widgets with respect to the small aggregated course dataset are the following.

5. Discussion

5.4.1. Logins over Time

Figure 5.3 shows the successful logins over four weeks, including the test phase of the Law Busters MOOC. Its official course start on the 13th of December does not show a high number of logins in the data. The weeks prior, where announcements and promotion for the course were made, have an observable higher number of logins. The impact of early subscribers to the course, before the official start date, can be observed in the widget. The time frame within the course was offered shows less logins on its first weekend, and a distinct rise of login numbers at the beginning of the second week (around the 18th of December). When looking at the selected weeks of data, the first thing the target user group noticed, is the distinct decline of logins in December.

There one needs to take additional external influences into account: Christmas and the related public holidays. For most of the attendees the time between 24th of December and New Year's Eve seems to be family time. They might be travelling, having no access to the course platform or enjoying time offline. Additionally, students of Austrian universities have lecture free days, starting before Christmas, ranging until the 6th of January. The steady rise of logins after the first few days of January is clearly observable, with people returning to school and work and picking up and increasing learning efforts where they left off in the previous year.

The Law Busters MOOC released new lecture content on Thursdays, three times, the upload on this day is not reflected with login numbers. Release dates could not directly be observed to have influence with this displayed metric, for other course formats or a larger target audience group this might differ.

An important takeaway from the *Logins over Time* widget is, that it is important to consider additional events which could relate to the logins, in this case the public holidays. This guideline especially holds true if there is a noticeable outlier in the login numbers, where filtering the data for different time frames might put the absolute numbers in more perspective and help teachers identify if certain events really have that big of an impact or not.

5.4. Widget Feedback

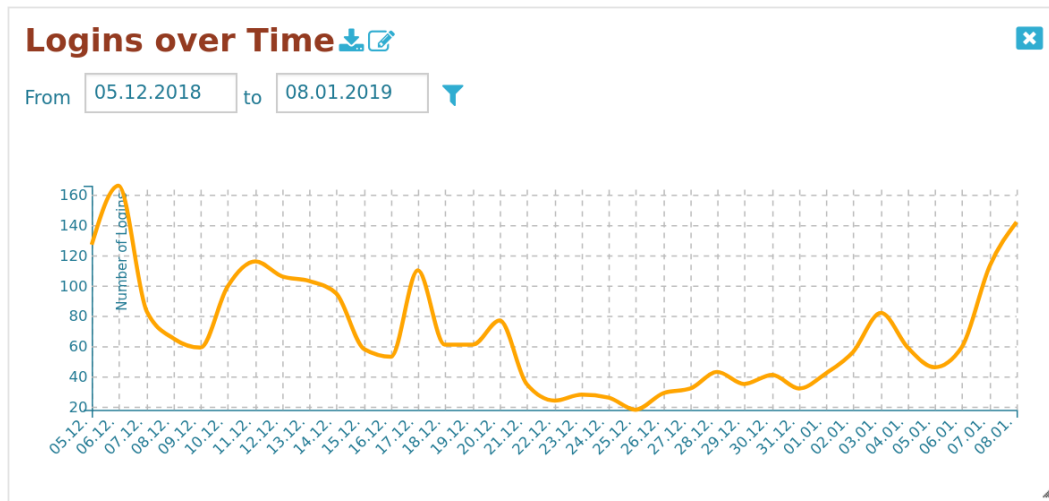


Figure 5.3.: LA Cockpit Law Busters Logins

5.4.2. Forum Posts

From the group of MOOC participants only a small group participates actively within the provided course forum. The Law Busters tried to engage with its learners with some form of introduction task, which lead to the group of 12 learners that posted once, visualized as the outer ring in figure 5.4. Courses which explicitly foster interaction and discussion might lead to higher numbers. The number of attendees does not automatically result in more active discussions, this can be verified when comparing the Law Busters to a course about ten times the participant size (inner circle of figure 5.4). Engaging users in MOOCs in forum discussions is known to be a hard task, so the numbers in this widget will most often proof that most of the participants only post very little to once or not at all.

5. Discussion

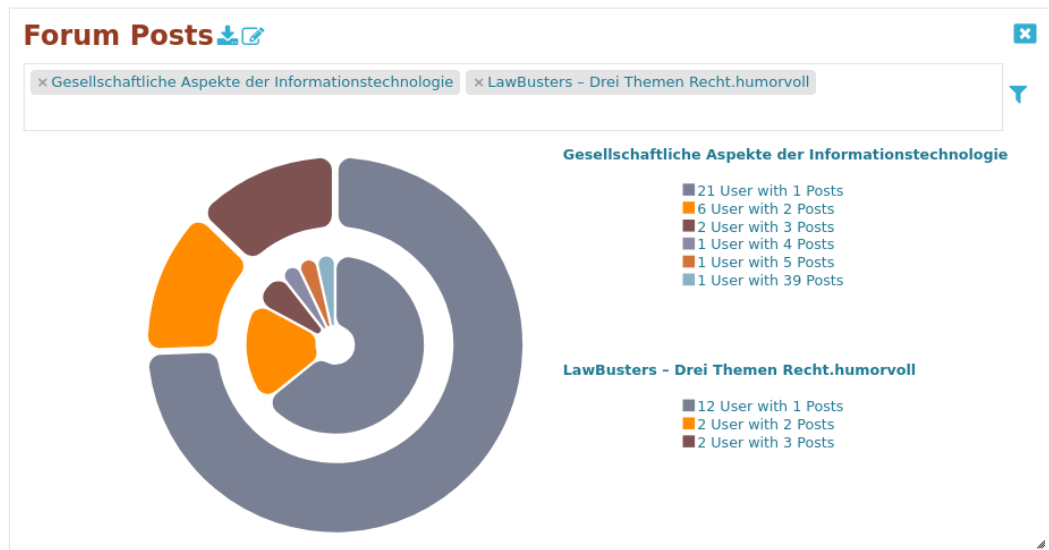


Figure 5.4.: LA Cockpit Law Busters Forum Posts

5.4.3. Device Statistics

The three different pie chart visualizations of the *Device Statistics* widget are discussed separately, although the datasets and displayed numbers are interconnected.

For the Law Busters MOOC, the used platforms and operating systems numbers from the *OS selection* in figure 5.5 show a broad range of platforms used. Nearly half of all aggregated visits were made with an Windows operating system (Win 32, 1363 Visits), followed by two thirds of Apple devices (identified with MacIntel, 879 Visits). The remaining third accessed the course either with various Linux operating systems (desktop versions), or mobile devices with Android (Linux armv71, Linux armv81) or Apple, 45 Visits via iPhone and 10 Visits with iPad. The distribution itself is to be expected, with less users on mobile devices than one could assume nowadays. Featuring large screens, keyboards or increased computing power, desktop computers seem to be favoured by most of the Law Busters participants.

5.4. Widget Feedback

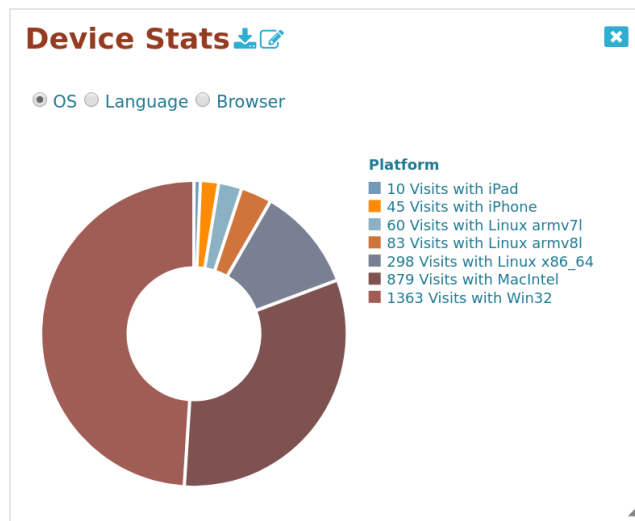


Figure 5.5.: LA Cockpit Law Busters Device Statistics Operating System

Operating systems usually ship their own browser by default, so Apple's Safari could be expected to lead the browser statistics in figure 5.6. Contrary to that assumption, there are two other major browser which the attendees use. Chrome in various versions was used for more than forty percent of the visits and nearly the same amount of users accessed the course homepage with Firefox, by Mozilla. The remaining twenty percent of site accesses are split between Safari (191 Visits), Internet Explorer and Microsoft's Edge (in total 243 Visits).

From the third dataset, displaying data on browser language settings, one could expect a dominating number of visits with German locales enabled. The Law Busters MOOC indicates, that roughly two thirds (figure 5.7) browse with German as main language enabled (de-AT, de-DE or de). The remaining third of users accessed the course with English locales en-US enabled. This does not lead to the conclusion, that only German and English are languages spoken, and/or exclusively used by the course visitors. It indicates the preferred option in which language any course content on the platform is accessed. The widget might show more nuanced numbers for other courses on the platform compared to the small user group of the

5. Discussion

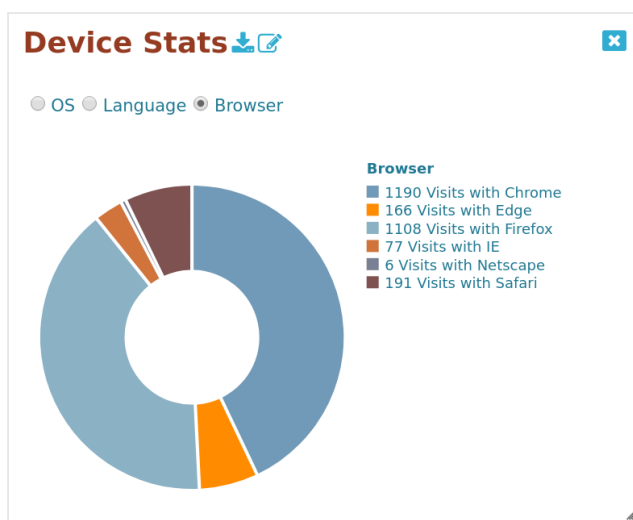


Figure 5.6.: LA Cockpit Law Busters Device Statistics Browser

Law Busters MOOC. In general, these numbers from the widget Device Statistics might help administrators of MOOCs when identifying technical issues or planning new features for the used platforms. Teachers might find the language dataset to be more helpful than the other two, especially in adjusting lecture material or helping to avoid language barriers from an early stage on.

5.4.4. Activity Calendar

This widget shows an aggregated number of activity within the course, indicating more activity by darker coloured squares. The *Logins over Time* widget does not directly relate to this activity metric. There are days with smaller number of logins but highly active users, whereas other days show many logins but very little activity. A possible example which leads to the last situation could be the login of many students on an announced day to check if grading results are available, directly followed by a logout and no further interaction when the grade is received.

5.4. Widget Feedback

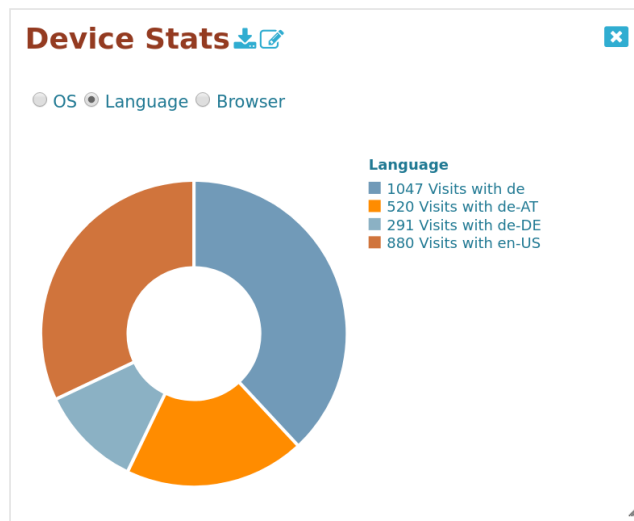


Figure 5.7.: LA Cockpit Law Busters Device Statistics Language

Looking at the Law Busters data in the *Activity Calendar* widget, figure 5.8, the middle of the week seems to feature more user activity than the other weekdays. The main influence here could be the starting week day of the MOOC. On a Thursday, the first video lecture was uploaded, subsequent upload and release of new video lectures happened in a weekly fashion, always on Thursdays. Featuring only a short period of three weeks, without further evaluation, one cannot reliably draw the conclusion from the Law Busters MOOC, that this repeating activity pattern from the initial starting day carries over to a larger time span of recorded user activity.

On the most active day, 55505 activities within the course were aggregated. The following month, February, contributes with numbers ranging between five- and ten thousand, only about a fifth of the maximum value from January. Exact numbers can be identified with the additional tooltips of the widget, where absolute aggregated numbers are displayed.

The pattern that release weekdays keep being more active days will definitely be noticeable in the initial course schedule. It will change in the following months of the MOOC, when for new joining course participants all lecture content is available from the start on. A longer aggregation

5. Discussion



Figure 5.8.: LA Cockpit Law Busters Device Activity Calendar

period will lead to better visualization within the widget, but one can already classify two different groups of user activity. Learning activity patterns differ between the learners joining within the initial phase and learners joining later on.

The widget provides a long-term evaluation method on user activity and might be helpful for teachers over the course of a whole semester. For the widget itself, a cross evaluation with other course formats might lead to new insights, whether weekdays in general are more active days and weekends are low on activity to eventually conclude on learners' preferred days to consume course content.

5.4.5. Heatmap

The widget itself aggregates various heatmaps over the distinct course URLs, as described in section 3.4.3. Each used browser window size and course URL combination is listed as individual heatmap. Looking at the browser size resolutions used to access the Law Busters course, there are two things to observe:

5.4. Widget Feedback

First, there are many similar, but only slightly differing resolutions. For example, up until the beginning of February, 6099 accesses with the window size 1280*618 and 7581 accesses with 1280*635 have been aggregated. These two groups have a minor window height difference, meaning that they could be considered equivalent in terms of displayed content. Nevertheless, the widget aggregates each distinct pair of window with and window height as item. The window sizes correlate to the screen size resolution, with users either accessing the course with a full-sized browser window or a smaller window size on a larger screen size.

Second, the most used browser window sizes are all combinations such as 1920*992, none below 1200 pixel window width. Similarly, the lesser used combinations are 360*616 or 689*433, and sizes below. This is a direct result from the observed *Device Statistics*, with desktop computers and larger available screen resolutions favoured over mobile devices/smaller screens when accessing the Law Busters MOOC.

The aggregated mouse activity in the heatmap itself leads to the following two observations within the course layout.

Low and Punctual Interaction

Denser points in the heatmap are visualized in red and are most often aggregated around interaction and menu items. The course layout features three distinct buttons to switch between the three offered video lectures, heatmaps such as figure 5.9, show a clear use of these buttons, but nothing more.

This low interaction, with anything but the bare minimum to access the course content, can be observed on more than half of the aggregated heatmaps. Furthermore, the areas of interaction are punctual and users seem to be goal-oriented, not interested in exploring anything else within the course website.

5. Discussion

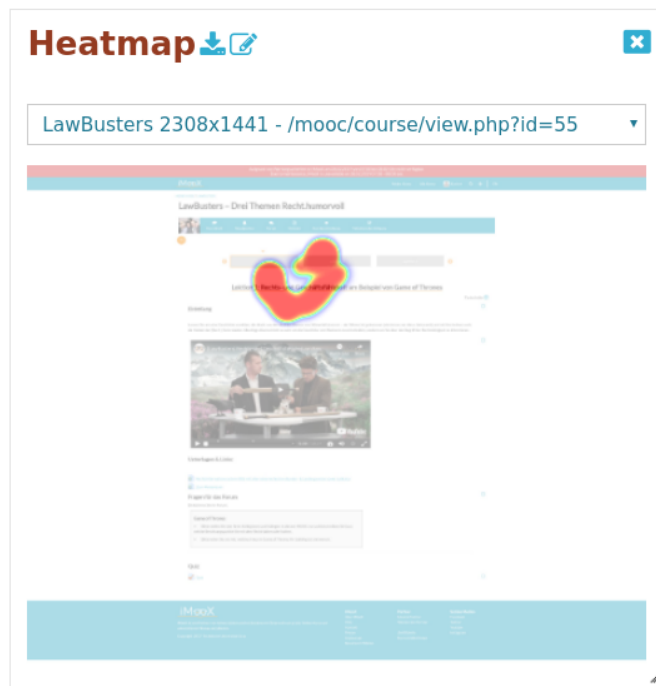


Figure 5.9.: LA Cockpit Law Busters Device Heatmap Punctual Interaction

Embedded Video Area is kept Interaction free

A very different picture of user activity can be observed by some heatmaps, with two examples given in figure 5.10 and figure 5.11. Less than a third of generated heatmaps feature such similar impressions and mouse patterns. Within those heatmaps, there is significantly more mouse activity than in the previously mentioned low interaction example. The traces are distributed over the entire browser window, even down to the bottom of the displayed page, but the area of embed video content is kept clear. This area seems to act as mental barrier, with the traces relating to the users feeling the need to stay clear of the content area, keeping it free of the mouse pointer, or even feeling the urge to move it out of the way when consuming the video lecture. The aggregation of activity data over all users does not lead to heatmaps where distinct denser areas of video controls being used

5.4. Widget Feedback

could be identified. Such smaller areas of interest could better be tested and verified in a lab environment, with restricted tasks or individual trace aggregation.

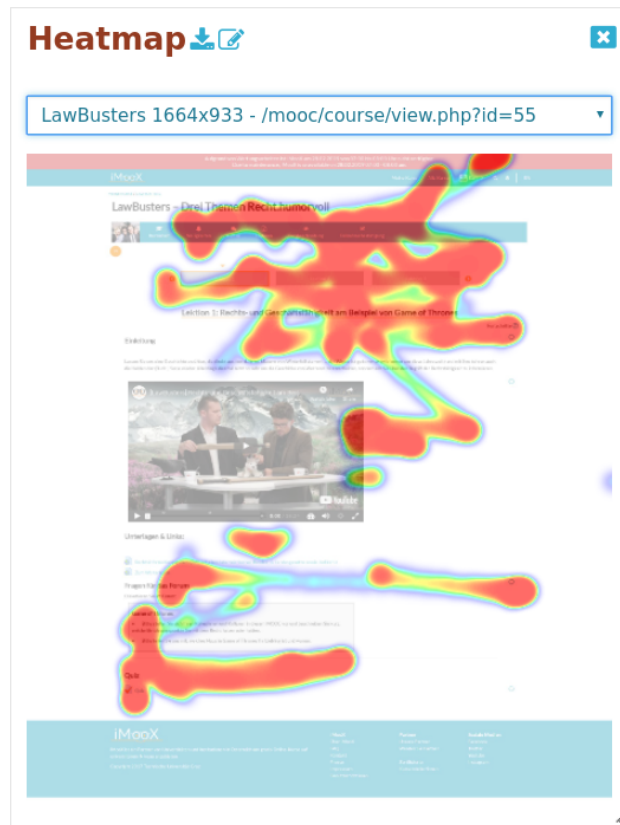


Figure 5.10.: LA Cockpit Law Busters Heatmap Video Area Example 1

The course page of the Law Busters MOOC featured a small set of video lectures and less content to scroll down through. For this setting, users consumed most of the content available. It was not possible to reliably detect that users only consume the first part of a website and avoid to scroll. For smaller window and screen size resolution, the recorded interaction overall reduced, was more dense and focused on most important interaction and menu buttons. Mobile devices and responsive layouts support this behaviour in general.

5. Discussion

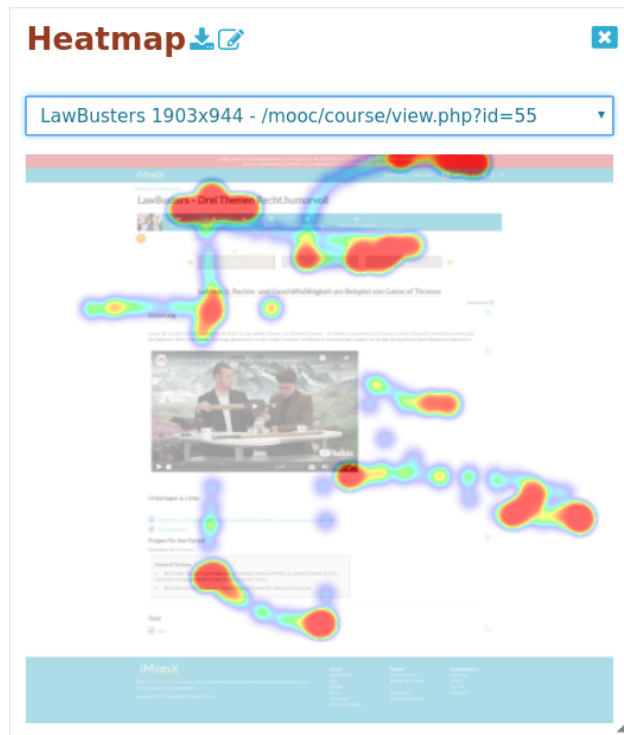


Figure 5.11.: LA Cockpit Law Busters Heatmap Video Area Example 2

The *Heatmap* widget gives new insights into the use of lecture content, with varying results. The provided screenshots make interpretation possible and easier, nevertheless the end product of a process is visualized. Therefore it might be hard for teachers to identify the reasons which lead learners to the aggregated activity traces.

The final chapter will give an outlook on where to put future work and on which of the improvement ideas the tools could focus, as well as concluding on the work done with the web analysis of the WA Plugin and visualization and improvements done within the LA Cockpit.

6. Outlook and Conclusion

Particularly from the target user group of researchers and administrators valuable input and further ideas to improve the LA Cockpit was received. The focus of these feature requests is of an abstract nature, related to the metrics and the data, rather than the application of the widget themselves. Even so there were mutual interests which can be summed up as the following main requests:

- include touch compatibility
- include video analysis and metrics
- research aggregated data with knowledge discovery methods
- provide thorough evaluation

There is a strong need for a larger evaluation of the LA Cockpit including a significant test user group. Not only letting the target user group give feedback as about what information they want to be presented with, but evaluating how actionable output is produced would be the next step of the development cycle. Efforts should be made to evaluate the tool in terms of interface design, user experience and -friendliness as well as in terms of the content displayed. This can be done with improvements on technical side, where addition of new widgets will be a quick next step in supporting the future use of the LA Cockpit.

In terms of using what is already there, the data traces from the behavioural analysis could prove to be a challenge for interested researchers. Giving further research incentives or comparing this real-life-data set to laboratory settings might provide ideas and scientific foundation for further metrics or even additional data sources to be supplied by the WA plugin.

6. Outlook and Conclusion

Activity is the central abstract measure the LA Cockpit bases its metrics on. In addition to the WA plugin and its extension, the related topics of video analysis can be incorporated. Video lectures are a main transfer method of learning content, often mixed with interactive elements such as quizzes. The idea is to get better insight into the users' behaviour when consuming these learning content is a promising next step.

The more options a Learning Analytics tool offers, the more important a clear definition of the displayed data, metrics and the reason for the visualization needs to be given. A Frequently Asked Questions Section giving background on Learning Analytics, the inner workings of the tool and the design decisions of the widgets' visualizations could prove beneficial to the target user groups.

With the LA Cockpit it is possible to provide valuable insight for MOOCs. The widgets and its metrics provide easy accessible information to derive information about the courses, the learners and their interaction with the course content from. The perspective for the tool's future use and conclusions are discussed in the last section.

6.1. Conclusion

The Open Source learning management system Moodle provides a suitable environment for Massive Open Online Courses. For iMooX, the Austrian platform for MOOCs, a custom Learning Analytics tool called *LA Cockpit* has been deployed. The need for additional information and insights stems from the nature of the online courses themselves. Massive, as in many learners and distant, as in accessible online, they provide a very different learning environment compared to face-to-face classrooms. For teachers and instructors such courses present a challenge to address the administration and support of their learners with the same traditional principles they are used to. Feedback is available in implicit form rather than explicit and can not directly be observed. Learning analytics can provide a set of tools for transferring this knowledge.

6.1. Conclusion

This is also where the WA Plugin bridges the gap in the learning process between teachers and students. With respect to the target user group, it is important to carefully decide which analytics should be displayed. The focus of the LA Cockpit was to make it into a modular framework, making it easily maintainable and extendable. Therefore, the tool offers a broad range of metrics. Additionally it covers the aggregation of the data and the visualization.

The LA Cockpit includes basic key figures related to the learning management system itself (e.g. logins over time). With the addition of the so-called Web Analytics plugin it is possible to aggregate data traces related to the activity of users within courses. Behavioural analytics let the target user groups infer on the way students learn with the provided course materials. Utilizing Learning Analytics is no silver bullet, generally there is no easy "one size fits all" approach, therefore the LA Cockpit features a set of tools and offers a highly modular dashboard, customizable to the different needs of the target user groups.

Based on a plugin structure the WA Plugin employs a range of metrics to capture user activity. This behavioural analysis is done via the aggregation of different input device traces left by the user within the browser. Aggregating an array of events and actions, three widgets have been designed to visualize metrics within the dashboard. Statistical information about the used devices, browser versions and language settings is provided by the widget *Device Statistics*. The widget *Activity Calender* adds a temporal visualization element to the data. Displayed as a daily calendar for the last 12 months, different coloured squares match activity levels. With this view, it is possible to reveal reoccurring patterns of user contribution within online learning courses, possibly so far unnoticed. The widget *Heatmap* employ the traditional concept of mouse activity heatmaps, where more frequently hovered regions are shown in red. Often used as a tool to validate the user experience with websites regarding their design, the widget offers another dimension of information. Resources most often used as well as the regions of high interest can be visually inspected and give a fast overview to teachers and administrators.

6. Outlook and Conclusion

As these widgets need to visualize complex coherences, the LA Cockpit uses state-of-the-art technology with the framework of D3.js. All visualizations within the tool follow the core guidelines of dynamic and interactive display. With this concept, it is possible to let the user explore the data themselves rather than presenting them with indicators hard to understand and interpret. This exploration phase is crucial in letting the user grasp coherences otherwise not understandable due to big datasets or blurred by aggregated averages without the real data set. All metrics feature course-wide aggregation of data, focussing more on the learning process than the individuals' learning trace. The additional privacy created by that does not affect the quality of information provided by the tool.

The thesis shows that these type of interactive visualizations are an important component when transferring statistical key figures and Learning Analytics. The information to be displayed need to be defined clearly (e.g. within metrics) and adapted for the target user group. Valuable insight can be generated when the target user group can act after inspecting the data available and infer their actions from that. This is a central effort in improving the underlying quality of learning materials and the learning process.

Continuing the path of previous research on Learning Analytics within iMooX, the LA Cockpit is Open Source and designed with extensibility in mind. Other developers are encouraged to add their metrics and enlarge the repertoire of insights with widgets. It is even possible to transfer the tool to a completely new target group, when changing the focus of metrics to students. Building a student-facing dashboard version of the LA Cockpit would be feasible by reusing the core components of aggregation and visualization. Eventually, the tool allows quantifiable insight into the learners behaviour and their process of learning with MOOCs on the iMooX platform.

With the LA Cockpit and the WA Plugin a suitable framework for Learning Analytics was created. Such tools are essential for bridging the information gap between students and teachers in distant online learning courses, as the nature of MOOCs provides implicit feedback in abundance contrary to explicit feedback. Continuing research on this will proof beneficial, because

6.1. Conclusion

the findings can be transferred into general e-learning environments, which gain in importance over traditional learning models.

Further development and research can improve these widgets and add features to the tool. The incentive for meaningful additions directly stem from the offered courses. Video lectures or quiz content will provide motivation for aggregating key figures on aspects such as "numbers of video lessons watched" or "minutes of video lectures consumed". With video lectures being a core component in transferring learning content, the next promising steps are analytics of video consumption. This intersects the behavioural analysis provided by the WA plugin and provides the chance of further insights into the consumption of video content within MOOCs. Followed by deeper evaluation of the interface design, modifying the existing metric's visualization and providing alternative types offers chances to increase user-friendliness and satisfaction.

Future research and improvements of the LA Cockpit should not only close the feedback loop to help learners in their learning process but bridge the gap between productive use and research. Being an actively used tool on platforms such as iMooX gives it the chance for a qualitative insights on how Learning Analytics are applied by its target user groups. The research community can benefit from this as most of the tools never leave their prototype stadium. With this next possible steps the path of the LA Cockpit sets out to improve its own feature set but more importantly to re-establish the information channel between learners and teachers in online learning environments. This means that teachers can adapt their knowledge of helping and improving the learning process with the means of current technologies, for a bigger set of students than the traditional classroom setting would have allowed them. This approach mirrors the basic aim of Learning Analytics, to improve all possible parts of the Learning Analytics life cycle itself and let all involved stakeholders benefit from its application.

Appendix

Appendix A.

A.1. Additional Libraries

In this section a short introduction of the used technologies and libraries will be given. For full reference, additional used libraries and their purpose are listed in the following paragraph. Whereever necessary, third party libraries were used to provide enriched user interaction whilst maintaining a small efficient open source code base of the plugin.

select2.js

Licence MIT

Purpose Multi-Select jQuery Boxes

The JavaScript library `select2.js`¹ provides a highly customizable select box with support for searching, tagging and other highly used features. Having long lists of selectable items, such as course names, users will appreciate the provided comfort of the filter and tag system. The `select2.js` is available as AMD Module and is built together with the plugin's JavaScript functionality.

¹<https://select2.org/>, last accessed: February 22, 2019

Appendix A.

jquery-collision.js

Licence MIT

Purpose jQuery extension to check collisions between selectors

With this MIT licensed jQuery extension well known features for a collision free dashboard interaction are provided.² It prevents overlap of important information when resizing or dragging widgets.

jquery-ui-draggable-collison.js

Licence MIT

Purpose jQuery UI extension to check collisions of draggable selectors

Together with `jquery-collision.js` overlapping windows on the dashboard of the LA Cockpit are prevented.³

jspdf.js

Licence MIT

Purpose Client Side PDF Generation with JavaScript

The PDF Report is fully generated on the client side, meaning that the widgets are rendered from within the browser with the help of jsPDF⁴

simpleheat.js

Licence BSD-2-Clause "Simplified" License

Purpose Generation of heat map canvas

²<https://github.com/dsbaars/jquery-collision>, last accessed: November 1, 2017

³<https://github.com/dsbaars/jq-ui-draggable-collision>,
last accessed: November 2, 2017

⁴<https://github.com/MrRio/jsPDF>, last accessed: January 29, 2019

A.2. Database Tables Layout

The LA Cockpit widget Heatmap uses the `simpleheat.js`⁵ to build the color values and map structure to display on top of the aggregated screenshots of course URLs.

A.2. Database Tables Layout

Column	Type	Comments
<i>id</i>	bigint(10)	dashboard id
userid	bigint(10)	owner of the dashboard
savedname	longtext	user selected name

Table A.1.: Structure of `mdl_local_lacockpit_dashboards`

Column	Type	Comments
<i>id</i>	int(11)	widget id
type	text	widget type
xpos	bigint(10)	widget x position on dashboard
ypos	bigint(10)	widget y position on dashboard
width	bigint(10)	current width of widget
height	bigint(10)	current height of widget
filter	text	filter preferences of widget
dashboardid	bigint(10)	dashboard id the widget is added to
pdfremarks	longtext	note section

Table A.2.: Structure of `mdl_local_lacockpit_widgets`

⁵<https://github.com/mourner/simpleheat/>, last accessed: January 29, 2019

Appendix A.

Column	Type	Comments
<i>id</i>	bigint(10)	id log entry
timestamp	bigint(10)	UNIX Timestamp of event
courseid	bigint(10)	course id
bl	longtext	browser language
bpf	longtext	browser platform (OS)
bn	longtext	browser name
bv	longtext	browser version
bu	longtext	full string of user agent

Table A.3.: Structure of mdl_block_wa_browser

Column	Type	Comments
<i>id</i>	bigint(10)	id log entry
timestamp	bigint(10)	UNIX Timestamp of event
eventtime	double(20,0)	JavaScript precision time stamp
courseid	bigint(10)	course id
wl	longtext	course URL
xpos	bigint(10)	mouse pointer x position
ypos	bigint(10)	mouse pointer y position
wwidth	bigint(10)	width of browser window
wheight	bigint(10)	height of browser window
maxpagesize	bigint(10)	maximum scroll height of page

Table A.4.: Structure of mdl_block_wa_browser

A.3. Heatmap Screenshot Generation

Listing A.1: Node.js file controlling headless chrome

```

1 // LA Cockpit Puppeteer to start headless chrome
2 // to screenshot webpages for the activity widget
3
4 const puppeteer = require('puppeteer');
5
6 //arguments from commandline
7 const url = process.argv[2];
8 const mywidth = parseInt(process.argv[3], 10);
9 const myheight = parseInt(process.argv[4], 10);
10 const filename = process.argv[5];
11
12 if(!url) {
13   throw("Please provide a URL as the first argument");
14 }
15 if((!mywidth) || (!myheight)) {
16   throw("Provide width/height for browser/viewport configuration");
17 }
18 if(!filename){
19   throw("Provide filename to save screenshot");
20 }
21
22 console.log("... LA Cockpit making screenshot ... ", mywidth,
23   "* ", myheight);
24
25 (async () => {
26   //note: no sandbox necessary for most linux systems
27   const browser = await puppeteer.launch({
28     args: ['--no-sandbox', '--window-size=${ mywidth },${ myheight }']
29   });
30   const page = await browser.newPage();
31   await page.goto('http://www.imoox.at/login/index.php?tab=1');
32   await page.setViewport({width: mywidth, height: myheight});
33   await page.type('#username', process.env.IMOOX_USER);
34   await page.type('#password', process.env.IMOOX_PWD);
35
36   await page.click('#loginbtn');

```

Appendix A.

```
37 await page.waitForNavigation()
38 await page.goto(url)
39
40 await page.screenshot({path: filename, type:"jpeg", fullPage:
    true});
41 await browser.close();
42 })().then(function(){
43 console.log("Ignore possible user access error")
44 });
```

Appendix B.

B.1. PDF Report of a Law Busters Dashboard

Report

Learning Analytics Cockpit

generated on 22/02/2019

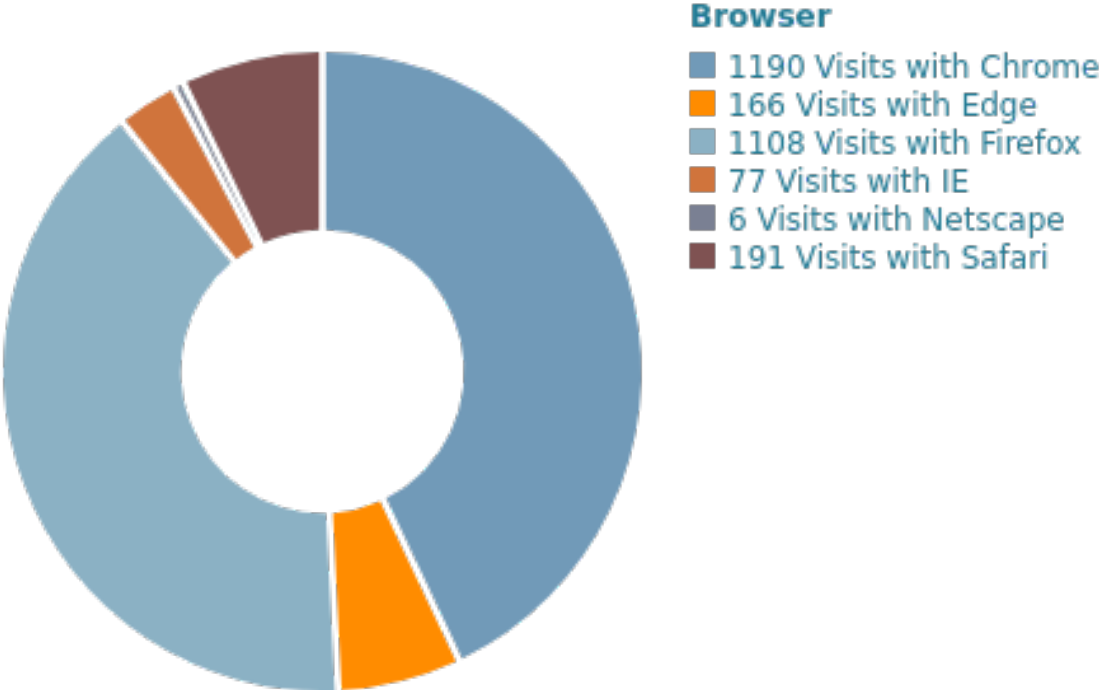
Heatmap



Mouse Activity Data from the additional Web Analytics plugin is visualized in a classic heatmap with underlying page screenshots, for each pair of resolution and page combinations aggregated.

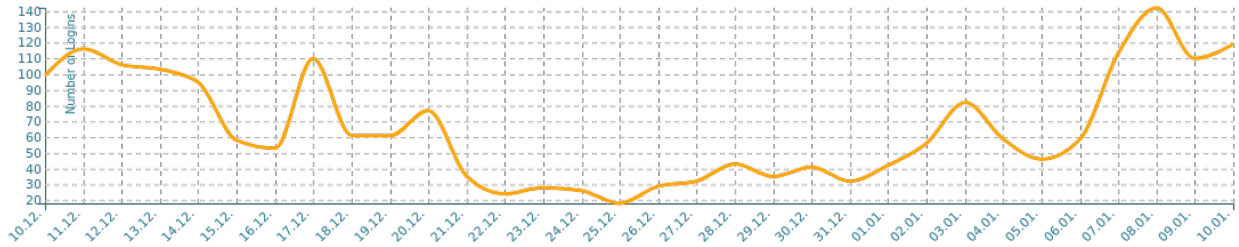
Note: either small interaction area or wide use of mouse

Device Stats



Data from the additional tracking plugin, displaying browser user agent, language and platform (OS).

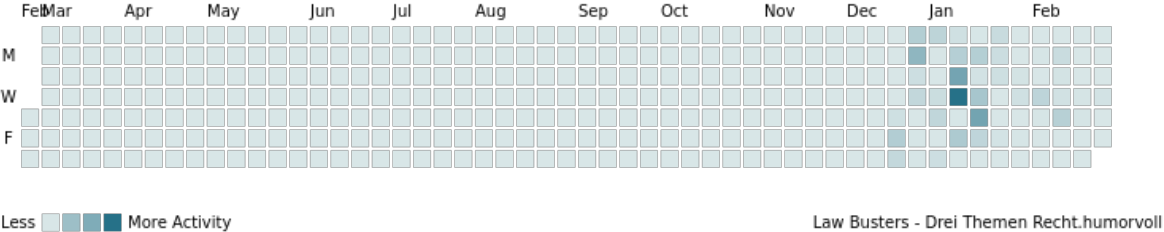
Logins over Time



The metric Logins over Time indicates the distinct successful logged in events from the system. Specific user data tied to the logins is not considered. Temporal data is filterable, please consider appropriate time frames for exporting chart data.

Note: Christmas Holidays, students will return after 6th of January, increase of logins to be expected

Heatmap Calendar



Tracked Activity Data visualized in a calendar view, similar to the Github Contribution Graph. As Acitivity any logged interaction from the additional tracking plugin is considered and counted.

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