Monitoring Learning Activities in PLE Using Semantic Modelling of Learner Behaviour

Selver Softic[1], Benham Taraghi[1], Martin Ebner[1],
Laurens De Vocht[2], Erik Mannens[2], and Rik Van de Walle[2]

[1] Graz University of Technology - Department for Social Learning
Muenzgrabenstr. 35A, 8010 Graz, Austria
{selver.softic,b.taraghi,martin.ebner}@tugraz.at
http://www.tugraz.at
[2] Ghent University - iMinds - Multimedia Lab
Gaston Crommelaan 8, 9000 Ghent, Belgium
{laurens.devocht,erik.mannens,rik.vandewalle}@ugent.be
http://www.ugent.be

Abstract. We report on the reflection of learning activities and revealing hidden information based on tracked user behaviour in our widget based PLE (Personal Learning Environment) at Graz University of Technology. Our reference data set includes information of more then 4000 active learners for a period of around two years. We have modelled activity and usage traces using domain specific ontologies like Activity Ontology and Learning Context Ontology from the IntelLEO[1] EU project. Generally we distinguish three different metrics: user centric, learning object (widget) centric and activity centric. We have used Semantic Web query languages like SPARQL and representation formats like RDF to implement a human and machine readable web service along with a learning analytics dashboard for metrics visualization. The results offer a quick overview of learning habits, preferred set-ups of learning objects (widgets) and overall reflection of usages and activity dynamics in the PLE platform over time. The architecture delivers insights for intervening and recommending as closure of a learning analytics cycle[1] to optimize confidence in the PLE.

Keywords: PLE, Semantic Web, Learning Analytics, Reflection, RDF, SPARQL.

1 Introduction

The Web 2.0 introduced intensive and wide-spread participation in online activities: the Social Web became a reality and derivate of such circumstances are visible nowadays in form of social networks (e.g. Facebook, Twitter), resource sharing platforms or interactive collaborative environments for problem solving [2,3]. The transformation of internet from consuming into interacting medium

[1] http://intelleo.eu

A. Holzinger et al. (Eds.): SouthCHI 2013, LNCS 7946, pp. 74–90, 2013.

along with the corresponding web technologies determinates more and more how we think, inform ourselves, organize our every day activities but also how we learn. This evolution is bringing new approaches to education. Massive Open Online Courses (MOOCs) for example aim for large-scale worldwide participation. This became possible on the one hand thanks to advances in the technology and on the other hand by challenges resulted by organising the education in general in order to provide to the needs of modern learners adequate time contemporary environments. The idea about open knowledge and open access also contributed to the developments in this direction. E-Learning platforms turned to be more efficient for tackling the problem of organisational and cost-effective matter[2]. Since the Web became not only consuming but also a producing medium evolving problem of Big Data is one of the next challenges for E-Learning to tackle in the near future. Limited availability of resources along with a time efficiency focus forces the designers and decision makers of learning platforms to revise their methodologies and techniques in order to respond the challenges of time and the needs of their targeted groups. On the other side learners are expecting a focused and simple way to organize their learning process, without losing time on information and actions which could disturb or prolong their learning, which also has a strong impact on acceptance of such platform [4].

Therefore todays learning process became more individual, multi faceted and activity driven with the tendency to ad-hoc initiated collaboration and information exchange. These circumstances imply the need for a scalable, adaptive learning environment enriched with multimedia supportive materials, communication channels, personalized search and interfaces to external platforms from Social Web like e.g. Slideshare, Youtube channels etc. All these parameters increase the complexity of online learning platform design and organization. Dynamics involved in this process require nowadays shorter optimization cycles in adaptation process of Learning Management Systems and Personal Learning Environments. In order to provide the learners an attractive surrounding and to tackle the named problems use of learning analytics for optimization of learning process and design of learning surrounding emerges as the time passes by. Personalized Learning Dashboards with focus to the learning objectives are necessary. Additionally learning platforms need a more focused view on overall learning management system performance and activities. Growth of data produced as monitoring material to the common state of the art learning platforms reveals a new dimension of optimization possibility to monitor the usage of learning artefacts and learning activities of users individually and overall aiming at the analysis of emotion and affective data in learning environments. Such data contributes to the personalization and adaptation of the learning process and deliver out of the results new interfaces for learning analytics.

Our widget based Personal Learning Environment (PLE)[3] was developed for the needs of Graz University of Technology. The PLE serves currently more then

[2] http://www.insidehighered.com/news/2012/10/16/u-texas-aims-use-moocs-reduce-costs-increase-completion
[3] http://ple.tugraz.at

4000 users. We tracked the usage, activities and the use of the learning Widgets. Widget-based interfaces have been considered by Reinhardt et al. to cope with learner awareness requirements as they allow dynamic addition of functionalities [5]. We used data collected over 2 years in order to generate learning analytics services with visualization support, which reflects the overall usage and process view on our environment following the research trends of previous years [6,7]. We want to gain insights [8] to optimize our PLE and adapt the PLE to the learners by using more personalized methods of learning possibilities e.g. through recommendations[9]. In the following section we introduce our findings and concepts based upon semantic modelling for visual data exploration to improve learning management systems with respect to social and semantic analysis of the determining parameters on a user, widget and activity centred level [10]. A PLE does not intend to substitute a Learning Management Systems (LMS), but it is an additional learning environment to support self regulated learning. So our model and analysis does not actually improve LMS, but it may have a role to improve the quality of learning by supporting students in their personal learning process. We model the learning context using domain specific ontologies and describe them semantically. We realize as such accessible interfacing and extendibility on machine and human level while offering advantages such as the possibility to enrich the analysis results with Linked Data[4]

2 Related Work

The current learning analytics research community defines [11] learning analytics as the analysis of communication logs [10,12], learning resources [13], learning management system logs as well existing learning designs [14,15] and the activity outside of the learning management systems [7,16]. The result of this analysis improves the creation of predictive models [17,18], recommendations [19,9] and refection [20].

Learning Analytics resides on algorithms, formulas, methods, and concepts that translate data into meaningful information. Modelling, structuring and processing the collected data derived from e.g. user behaviour tracking plays a decisive role for the evaluation. Different works outlined the importance of tracking activity data in Learning Management Systems [11,21]; none of them addressed the issue of intelligently structuring learner data in context and processing it to provide a flexible interface that ensures maximum benefit from collected information. Emerging technologies like the Semantic Web along with RDF[5] and SPARQL[6] where data is structured and queried as graphs and projected on specific knowledge domain using adequate ontologies. Linked Data has been fairly successful used to generate correct interpretation of webtables [22] and the DEPTHS environment demonstrates how a synergistic combination of

[4] http://linkeddata.org/
[5] http://www.w3.org/RDF/
[6] http://www.w3.org/TR/rdf-sparql-query/

social and semantic technologies and Linked Data advances the learning process in software engineering [23]. Additionally the Semantic Web introduces a retrieval standard: SPARQL, which enables easily querying of semantically enriched data. This potential is partly the topic of current research in the EU project *Intelligent Learning Extended Organisation (IntellLEO)* which produced in the published ontology framework: Activities Ontology [7] to model learning activities and events related to them along with the surrounding environment and Learning Context Ontology[8] which offers formalization of learning context as general learning situation. Due to their accuracy to the problem that is addressed by this work these ontologies have been used to model the context of analytic data collected used in following observations.

Our work focuses on tracking learner's widget activity in a PLE system. Further the reflection of different views on the trackers is tended to be presented using our learning analytics dashboard. Our method is based on a tracking model as a knowledge domain related context using Semantic Web ontologies and query languages like SPARQL similar to current research in the area of Self-regulated Learners(SRL)[24]. Exploratory graphics show that the sum of (web) user data on the access paths and the linkage of the resources within an environment (site) at a particular time window gives sufficient insight at what constitutes relevance; important properties and linkages between data resources[25]. The overall goal of is summarization of visualizations and evaluation of statistic data that enable the PLE optimization and present the research community used generic techniques and metrics for problems in design and adaptation of learning environments.

3 Use Case

In a PLE by definition there are no teachers and learners, producers and consumers like in Learning Management Systems (LMS). PLE lies in the category of self regulated learning where students have the whole control over the services and resources they may need and would like to use. Teachers may recommend their students to use some widgets or resources in PLE as they may recommend them to read some books, but they provide nothing in PLE.

3.1 Modelling Statistics of Learners Logs

Concept Modelling statistics in dimensions for the PLE: reflection (by tracking users), prediction (tracking activities) and unveiling hidden information (tracking widgets - LOs). All three dimension are directly in relation to each other which implies that reflection influences prediction and vice versa. The hidden information regarding the learning objects (widgets) is derived from these bidirectional bounds. This implication relies on modelling and the native concept of widget as learning object as it will be shown in following sections.

[7] http://www.intelleo.eu/ontologies/activities/spec/
[8] http://www.intelleo.eu/ontologies/activities/spec/

Revealing hidden information enables to find out how the learning process is going on in general and individually for each student in respect of what learners are learning: how often are they learning and whether it is continuously or not. This shows which learning objects are mostly used and hence is a possible indicator for usefulness.

Prediction: following the activities of learners, assumed that we can extract some patterns within activities (what they do and also what goals and to which extent they achieve a goal) teachers can predict the overall performance of their learners according to their activities.

Plotting the overall activities of learners reflects their learning process within PLE: this is reflection.

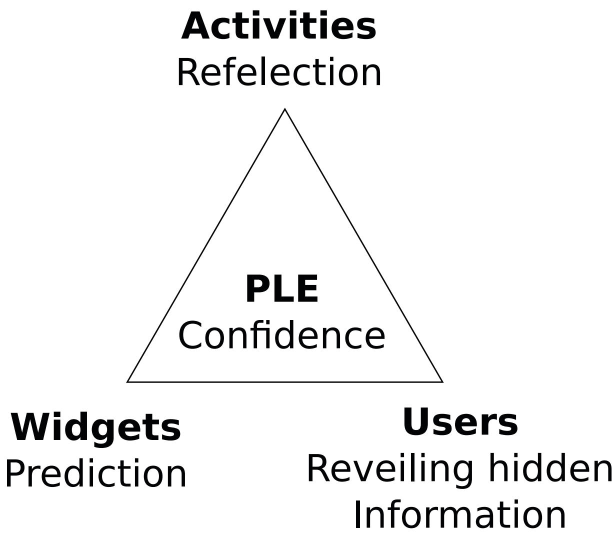

Fig. 1. `Dimensions of PLE` Measuring confidence by monitoring widgets, activities and users

Purpose. All statistics combined establish confidence in modules/widgets as interface between teacher (knowledge provision) and learner (knowledge consumer). The context of widgets is important to achieve reliable outcomes of the analysis of learner's activities. Figure 1 depicts the analysis of learner's activities ensures the optimization of the PLE focus to cover three modelling dimensions maximally by constructing a coherent view to support a call to action with high confidence.

Application. Specific use cases based on statistics learned on the modeled learners logs should: contribute to better understanding of PLE usage, and reveal favored designs of widget. Further intention that should be covered with this investigation is to orchestrate the insights into a recycling feedback loop to increase the overall acceptance of PLE as useful learning environment. Last targeted but not less important appliance of lesson learned should deliver initial information for improvements in our recommender system for widgets already integrated in PLE.

3.2 Dashboard for Analytics

Concept To get an overview, PLE administrators have access to a 'Dashboard' facilitating browsing the learning analytics from the PLE as shown in Figure 2. The dashboard contains views containing a graph visualization on the modelled information. The view is split in a summary which displays several graphs of measures derived from the raw statistics data to monitor the confidence and the balance of the learning environment.

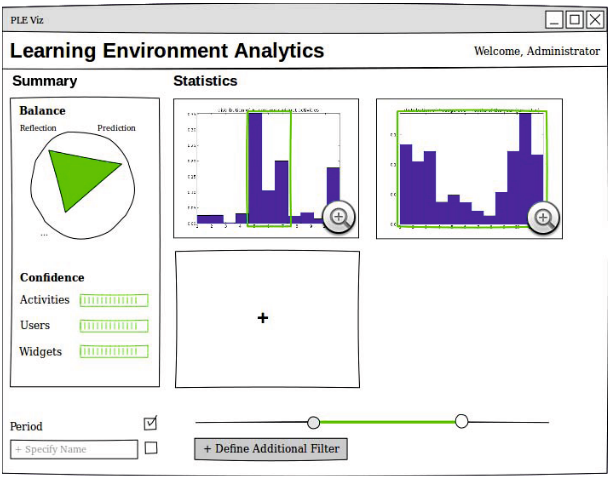

Fig. 2. `PLE Analytics Dashboard` Overview of the available statistics and measures of the PLE

Purpose. The dashboard is a collection of indicators for administrators to get to-the-point feedback. Administrators can deduct new views, broader or narrower; based on actions in the existing views because we allow intelligently adding new views on the statistics data to the dashboard. The combination of different views and visualizations of analytics based learner's log data encourages administrators to take action and further optimize the learning environment.

Application. The widget based interface for the dashboard guides users in constructing complex queries and revealing hidden correlations among the datasets. It is an excellent way for putting analytics into context using categories, assumptions, and reason towards relating perspectives in a broader context trough the addition and linking of multiple data resources.

4 Semantics for Learning Analytics

4.1 Modelling

In current work we are aiming at visualisation of three different kind of monitoring aspects interesting for optimisation of PLE: User centric view where relations between the learner and the learning surrounding along with aligned activities should be outlined. Activity centric view where activities bound to the widgets that a learner is using are tracked. Finally widget centric where the whole perspective is reflected out of the sight of learning widgets. With this purpose the data that was collected was tracked out of the PLE using simple log files which included information about a user (in anonymous way), about widget and activities related to the learning widget with additional time stamp when this logging event happened. Simple logging of data is unstructured and not easy queryable, the same problem is also with maintenance of such data. Generating specific visualization would in unstructured form imply formatting data into the form of visualisation interfaces and requires additional efforts for each new visualization framework that would be used for implementation of such monitoring dashboard.

In order to provide flexible data model that also delivers all wide accepted formats as e.g. XML or JSON as final output since those formats are very wide spread as input in visualization libraries our consideration lead us towards more operable and flexible data modelling framework and standards, for maintenance of tracking data. We wanted also to make the data model extensible and scalable, and to additionally enrich the data with the context reflection in which such data was collected. Since Semantic Web offers flexible and scalable approach to modelling, formatting data in this way was the next logical step. SPARQL as retrieval technology driven by the efforts of W3C community reached mature level comparable to common occurrences. Output of SPARQL frameworks support XML, JSON or comma separated values.

The challenge is to choose an adequate modelling vocabulary (in our case Ontology) since RDF offers only the framework how the data is aligned and organized in such constructions. Fortunately current research in *IntellLEO* EU project resolved our dilemmas. One of the main goals of this project is building an *innovative ontological framework for learning representation which includes learners, context and collaboration models, serving to achieve the targeted synergy*[9]. In the realm of the *IntellLEO* project inside the provided ontology framework two special ontologies are eminent. The first is the Activity Ontology which offers a vocabulary to represent different activities and events related to them inside of a learning environment with possibility to describe and reference the environment (in this case PLE) where these activities occur. The second contribution from current Ontology research work in *IntellLEO* project is the Learning Context Ontology which describes the context of a learning situation.

Our logs include the events about learners who use a PLE while performing different learning activities in a certain period of time. Their activities comply

[9] `http://intelleo.eu/index.php?id=5`

Listing 1.1. `LearningContext` in N3 RDF notation.

```
@prefix ao: <http://intelleo.eu/ontologies/activities/ns/> .
@prefix foaf: <http://xmlns.com/foaf/0.1/> .
@prefix lc: <http://www.intelleo.eu/ontologies/learning-context/ns/> .
@prefix rdfs: <http://www.w3.org/2000/01/rdf-schema#> .
@prefix um: <http://intelleo.eu/ontologies/user-model/ns/> .

<https://ple.tugraz.at/ns/activity/#Viewing> a ao:Viewing .

<https://ple.tugraz.at/ns/users/#FSKSN> a um:User;
    foaf:name "FSKSN" .

<http://ple.tugraz.at/ns/events/log/#7912> a ao:Logging;
    ao:performedBy <https://ple.tugraz.at/ns/users/#FSKSN>;
    ao:timestamp "2012-10-04T07:52:52" .

<https://ple.tugraz.at/ns/widgets/#LatexFormulaToPngWidget>
    a ao:Enivironment;
    rdfs:label "LaTeXFormulaPNG Converter" .

<http://ple.tugraz.at/ns/learningcontext/#7912> a lc:LearningContext;
    lc:activityRef <https://ple.tugraz.at/ns/activity/#Viewing>;
    lc:environmentRef
    <https://ple.tugraz.at/ns/widgets/#LatexFormulaToPngWidget>;
    lc:eventRef <http://ple.tugraz.at/ns/events/log/#7912>;
    lc:userRef <https://ple.tugraz.at/ns/users/#FSKSN> .
```

to our use cases very well, which implicitly solved our modelling vocabulary dilemma stated before. Representation of log entries from PLE as instance of a learning context concept can be seen in N3 RDF Notation in Listing 1.1.

As stated in listing 1.1 depicted instance of `lc:LearningContext` class descibes in compact N3 RDF Notation that a `ao:Logging` event occured which tracked the learning activity of `ao:Viewing` by certain `um:User` inside the learning widget named *LatexFormulaToPngWidget* as `ao:Enviroment` at certain time.

4.2 Querying

Beside the scalability and flexibility of data models Semantic Web also includes the advantage of traceability of such models using SPARQL. Common storage and retrieval systems for semantic data instances support the exposure of so-called SPARQL endpoints, where the data from the storages (RDF triple stores) can be easily retrieved by simple SQL like queries defined by SPARQL standard. Additional advantage of such endpoints is that most of them deliver result data in common formats like XML,JSON or comma separated values. This functionality is essential for processing the retrieved results for visualisation dashboard

Listing 1.2. `SPARQL` query filtering `Viewing` action on `LatexFormulaPNG` widget.

```
PREFIX ao: <http://intelleo.eu/ontologies/activities/ns/> .
PREFIX foaf: <http://xmlns.com/foaf/0.1/> .
PREFIX lc: <http://www.intelleo.eu/ontologies/learning-context/ns/> .
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#> .
PREFIX um: <http://intelleo.eu/ontologies/user-model/ns/> .

SELECT ?user WHERE
{
 ?x a lc:LearningContext;
      lc:activityRef <https://ple.tugraz.at/ns/activity/#Viewing>;
      lc:environmentRef
      <https://ple.tugraz.at/ns/widgets/#LatexFormulaToPngWidget>;
      lc:eventRef ?e;
      lc:userRef ?u.

 ?e a ao:Logging;
      ao:timestamp ?date.

 ?u a um:User;
      foaf:name ?user.

 FILTER ( ?date > "2011-01-01T00:00:00Z"^^xsd:dateTime )
}
```

(PLE-Viz). Also very important function is that the endpoints offer implicitly standardized interfaces based upon RDF for data exchange to other platforms. Operability over the data is much easier then in the case if the log data would be stored in specific structure without standardization. In this way humans and machines readable, reusable activity knowledge artefacts has been produced with broader appliance field then a simple tracking log entry.

Listing 1.2 depicts in the best way how easily a question like: "Which users performed viewing in *LaTeXFormulaPNG Converter* widget after the first of January 2011?" can be answered by simple SPARQL query. This approach obviously enables easy preprocessing and thanks to SPARQL endpoints output configuration, the desired inputs for visualizations can be delivered in the same step. Semantic Web uses a "closed world" representation which means if there are no results when there is no answer possible in the system. The advantages of Semantic Web technologies combined with adequate vocabularies and ontologies do not only support easy and flexible analysis, it extends the repositories to the outside world while implementing implicitly many interoperability options for external analytic systems.

5 Results

5.1 Visualization of Statistics

In this section we intend to describe some possible statistics that can be generated by the first prototype of PLE Analytics Dashboard. According to the PLE measuring confidence triangle described before, the statistics has been modeled into three dimensions. These dimensions are illustrated through some examples in the following sections. The dataset used to generate the following statistics contains the user log data of about last two years in PLE.

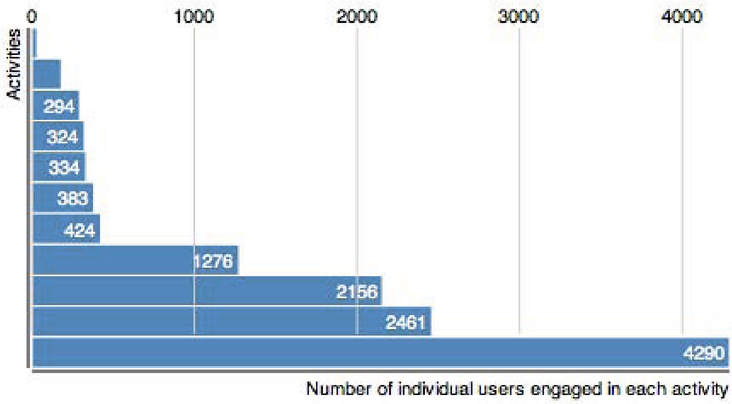

Fig. 3. `PLE statistics` Distribution of users over activities in PLE

User Centered. Each widget in PLE is associated to one or more activities depending on the functionality that is provided by the widget. To give an example, *Twitter* widget is associated to the activities *Reading*, *ContentSharing*, *DiscussAsynchronouly*, *Viewing* and *Search*. The other defined activities in PLE are *Authoring*, *Learning*, *Game*, *Quizzing*, *Computing* and *Listening*. Figure 3 depicts the distribution of users over all activities in PLE. The diagram illustrates that most of all users are engaged in the activities *Reading* (4290 users) followed by *Authoring* (2461 users) and *Search* (2156 users). In contrast *Listening* (33 users), *Computing* (181 users) and *Quizzing* (294 users) are rarely popular for users.

Widget Centered. Figure 4 demonstrates an example for widget centered statistics. It shows how often each widget is used in each period of time in PLE. The widgets *ZID News* (representing the actual news related to the Central Informatic Service), *TUGraz online* (Administration System), *TUGraz Newsgroups* (News groups), *TUGMail* (E-Mail service) and *TeachCenter Courses* (LMS platform) are listed on the top as the most frequent used widgets in the last two

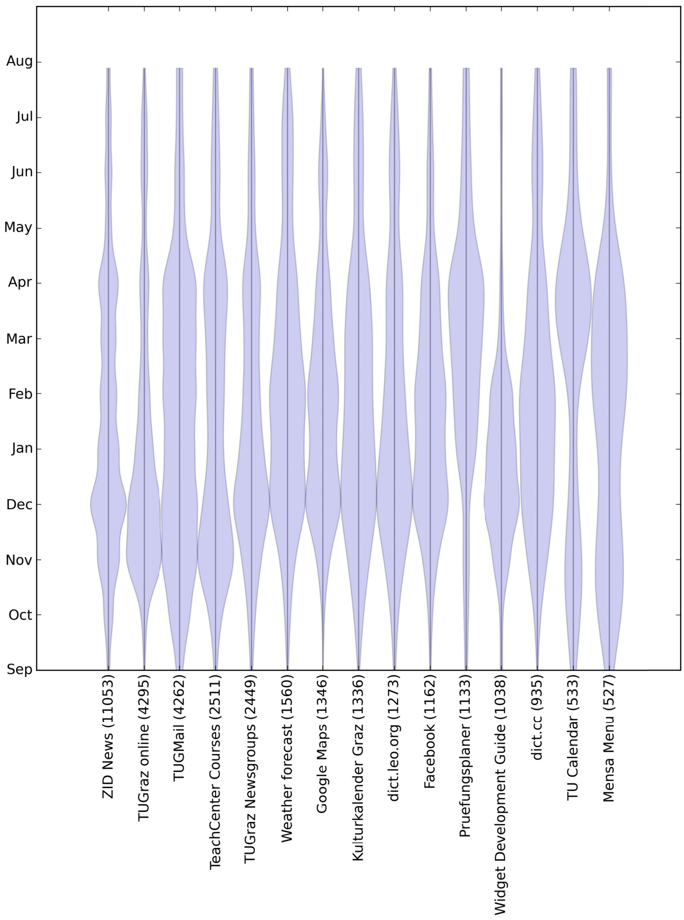

Fig. 4. `PLE statistics` Distribution of usage of the 15 most popular widgets each month in PLE

years. All these widgets represent university services that students daily use. According to the visualized statistics the highest range of user activity can be monitored from October (begin of the winter semester) until July (end of the summer semester). On the first week of January as well as in summer holidays no active usage cam be seen in PLE that is actually expected. The visualisation helps to detect widgets that are not popular at all or have been rarely used over the whole monitored period. Interestingly we can observe no significant change on this behaviour considering diffent period of times and different users. Widgets *Google Search*, *Address Book*, *Plane-Sweep Algorithmus* and *laengste gemeinsame Teilfolge* (a learning object to support learning the algorithm) are such examples that must be revised in a further development process. The other observations can be taken from this visualisation is the development of ple usage

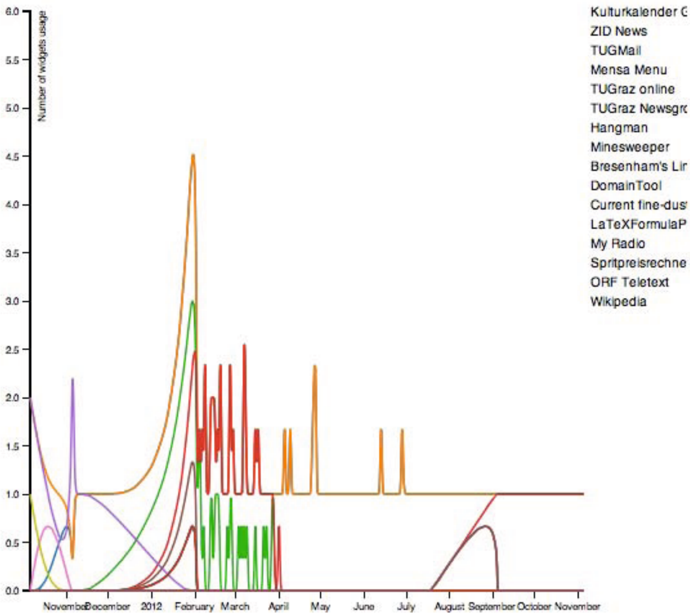

Fig. 5. `PLE statistics` Distribution of usage of widgets by a sample active user over time in PLE

in general during the time. It is obvious that the frequency and quantity of used widgets have been increased in year 2012 in comparison with 2011.

Figure 5 demonstrates an example that can be of high interest. It demonstrates the activities of a specific user during a time period (in this example over the whole monitored time). The sorted list of widgets that the user have been actively using can be seen on the diagram. It shows that the user has been constantly using some widgets (*KulturKalender Graz*, *ZID News* and *TUGMail*) since February 2012. *TUGMail* widget is an exception. The user has stopped using it from April to August 2012. Figure 6 demonstrates the activity of another user who uses only two widgets: *ZID News* and *TUGraz Newsgroup*. It is obvious that she has been using *ZID News* continuously.

Activity Centered. Figure 7 depicts the distribution of user activity over all activities in PLE. This diagram resembles figure 3 which depicts the distribution of users over all activities in PLE. The diagram shows that the activities *Reading* (28406 times) followed by *Search* (10588 times) and *Authoring* (9437 times) are most top popular ones. In contrast *Listening* (194 times), *Computing* (295 times) and again *Quizzing* (530 times) are rarely popular for users.

Figure 7 depicts the same situation over the whole monitored time period: an overall picture of the activity usage intensity. Again our observations from previous statistics can be confirmed. The list of activities on figure 7 are sorted

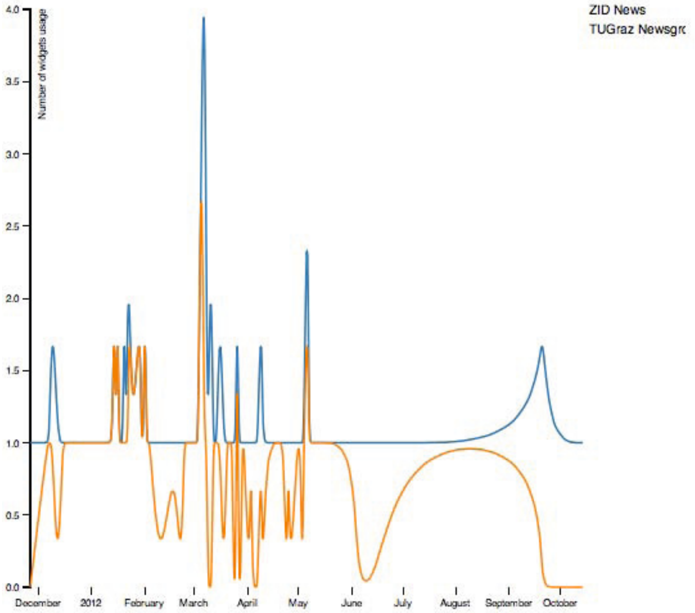

Fig. 6. `PLE statistics` Distribution of usage of widgets by a sample active user over time in PLE. Widgets: ZID News and TUGraz News

according to the popularity and dominance during the whole monitoring period. The same results can be achieved here.*Reading*, *Authoring* and *Search* are dominant activities, clearly seen in the year 2012 compared with 2011.

5.2 Discussion

The overview over distribution of activities can reflect the overall interest of the learners within PLE. It can be concluded that in case of our PLE users are more consumers that contributers. Visualisation of statistics can help to improve the PLE in general. Activities such as *Quizzing* and *Learning* (supported by some learning object widgets) are not quite popular. Our investigation showed that the corresponding widgets that support those activities must be revised in regard to some usability issues.

We can obtain a kind of rating/quality measure for the widgets that can be used as an indicator of likely future activity in the PLE. Distribution of usage of widgets over time in PLE showed exactly which widgets have been popular in certain period of time.

Widget centered statitics for a specific user reflect user oriented statistics on which widgets are favoured by a single user: We can observe if this trend is trackable over time or not. It delivers fast overview of affinities of single user

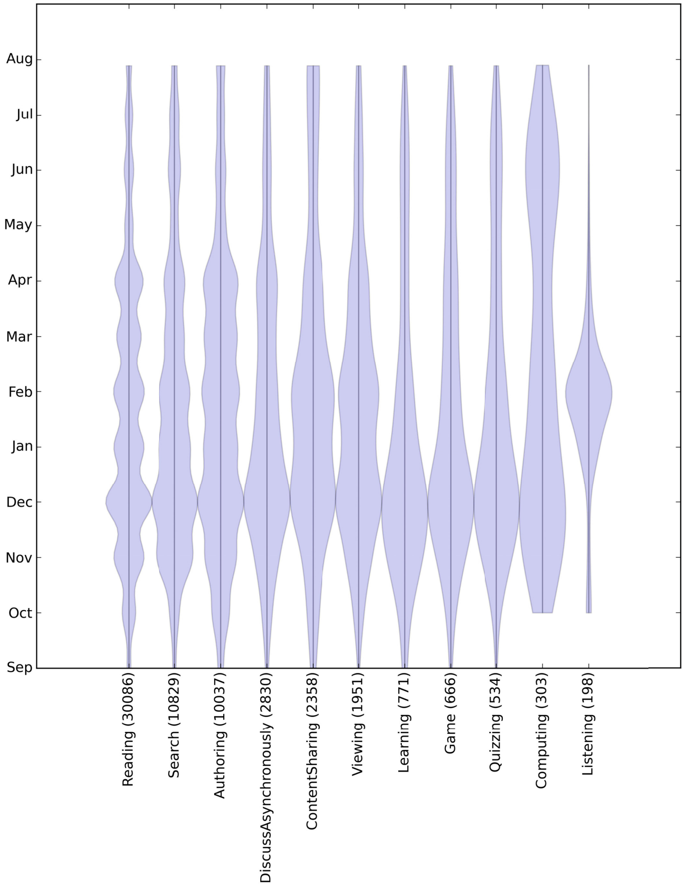

Fig. 7. `PLE statistics` Distribution of activities occurrence each month in PLE

considering the usage of special widgets. It can also be used e.g. as a basis for recommendation of new widgets in the widget store within PLE.

Through activity centered statistics we gain a better insight in the activities done in the PLE and their use. We can get insight about dominant activities, activity dissemination over time and activity peak usage periods.

6 Conclusions

The interactivity and relations between teachers and students has changed since the introduction of online technology such as the Web with environments such as PLE or LMS. The teacher is no longer the provider of knowledge but rather a middleman between information and student. Instead of being a passive knowledge consumer, the student has now become active in procuring, organizing and managing information. Further development of this technology helps students to understand concepts better and improve their skills.

We demonstrated that using semantic technologies enables the extensibility of learning analytics dashboards. Our approach generates uniform interfaces for information exchange, enables flexibility for visual analytics, and also includes the flexibility regarding the enrichment of learning analytics data with Linked Data. The spread of applicability covers wide range of analytics methodologies like prediction, reflection and as result of these the intervention field. Future efforts regarding improvement semantic structure data layer, besides the mentioned Linked Data could also include precisely defined categorisation of learning widgets, since PLE includes also this information. Especially the learning widget store as part of PLE could profit from this improvement.

The statistics visualisation help us to gain deep insight into the behaviour of a single user in a certain period of time .We showed examples what we have achieved with a PLE Analytics Dashboard. The statistics examples covered the user, widget and activity centered dimensions of the PLE confidence model we introduced. It is planned in near future to apply PLE Analytics Dashboard for some specific courses at university. The goal is to analyse the learner's behaviour in detail, the widgets they use or stop using for the given learning goals and map their monitored actions to their learning results. The main question will be how or if the PLE Analytics Dashboard must be further improved to meet these goals. The examples demonstrated for now show that it would be possible. We will do this survey as the next step in the near future.

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