Chapter 1
Analyzing Learner Characteristics and Courses Based on Cognitive Abilities, Learning Styles, and Context

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Abstract Student modeling and context modeling play an important role in adaptive and smart learning systems, enabling such systems to provide courses and recommendations that fit students' characteristics and consider their current context. In this chapter, three approaches are presented to automatically analyze learners' characteristics and courses in learning systems based on learners' cognitive abilities, learning styles, and context. First, a framework and a system are presented to automatically identify students' working memory capacity (WMC) based on their behavior in a learning management system. Second, a mechanism and an interactive tool are described for analyzing course contents in learning management systems (LMSs) with respect to students' learning styles. Third, a framework and an application are presented that build a comprehensive context profile through detecting available features of a device and tracking the usage of these features. All three approaches contribute toward building a foundation for providing learners with intelligent, adaptive, and personalized support based on their cognitive abilities, learning styles, and context.

Keywords Cognitive abilities · Learning styles · Context profile · Student modeling · Personalization

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1.1 Introduction

Learners have different backgrounds, motivation, and preferences in their own learning processes, and learning systems that ignore these differences have difficulty in meeting learners' needs effectively (Atman et al. 2009). Therefore, when designing instructional material, it is important to accommodate elements that reflect individual differences in learning. Learning systems that provide adaptivity and intelligent support based on learners' characteristics and situations have high potential to make online learning and teaching easier, and more effective for both learners and teachers (Tseng et al. 2008; Macfadyen and Dawson 2010). However, most of the popular learning management systems (LMSs) currently used by educational institutions, such as Moodle and Blackboard, do not provide adaptivity or intelligent support, neither for learners nor for teachers.

The aim of our research was to make learning systems more intelligent, adaptive, and personalized by analyzing online course structures and building comprehensive learner and context profiles that include various information about the learner and his/her context. Such analysis results and comprehensive profiles can then be used to extend learning systems with advanced adaptive and intelligent capabilities that provide personalized user interfaces, and adaptive course structures and recommendations. This book chapter focuses on the following three elements: learners' cognitive abilities, learning styles, and context. The approaches described in this chapter aim at gathering and provide information that enable learning systems to be adapt to the learners' cognitive abilities and learning styles, as well as the current context in which the learning occurs, leading to more effective, convenient, and successful learning experience.

One of the most important cognitive abilities for learning is working memory capacity (WMC) which affects students' learning behaviors to perform complex cognitive tasks such as reading comprehension, problem solving, and making decision (Broadway and Engle 2011). Providing students with course materials and activities by considering their WMC helps in avoiding cognitive overload and therefore positively affects students' learning (Gathercole and Alloway 2008). Traditionally, WMC can be measured by a variety of memory span tasks including counting span, operation span, and reading span which are related to the complex cognitive tasks (Broadway and Engle 2011; Unsworth et al. 2012). However, the main disadvantage of these measured tasks is that students have to do them in addition to their learning. In this chapter, we present a framework for automatically identify WMC from students' behavior in a learning system, which is described in Sect. 1.2.

Clay and Orwig (1999) defined learning style as a unique collection of individual skills and preferences that affects how a person perceives, gathers, and processes information. Making teachers aware of how well their courses fit with diverse learning styles can help them in improving their courses and providing personalized support for students with different learning styles. Sect. 1.3 illustrates

our mechanism for analyzing course contents in LMSs with respect to learning styles and a visualization tool to show the course support level for students' learning styles.

Data gathered from the usage of the learners' devices provide important information about the user and his/her context and can, together with the availability of device functionalities/features, be used to build a context profile (Chen et al. 2008). In Sect. 1.4, we introduce a framework that aims at building a comprehensive context profile, containing information about the devices a learner uses, the available functionalities/features on a learner's device as well as how frequently the respective device functionalities/features are used by the learner.

Section 1.5 concludes the chapter.

1.2 Identifying Cognitive Abilities from the Log Information of Learning Systems

The cognitive abilities are the abilities of the human brain to understand complex ideas, to adapt effectively to the environment, and to learn from experience (Broadway and Engle 2011; Park and Lee 2003). WMC, one of students' cognitive characteristics, is to keep active a limited amount of information for a very brief period of time (Miller 1956). Results of several studies have shown that students with low or high levels of WMC have very different performances on the different attention levels during performing cognitive tasks (Broadway and Engle 2011; Engle 2010; Gathercole and Alloway 2008). Knowing the levels of students' WMC can help in many ways to enhance learning and teaching in learning systems. Teachers can use this information to provide meaningful recommendations to their students. Furthermore, information about students' WMC can be used as input for adaptive systems to provide students with customized learning content and activities to suit their individual WMC. This section focuses on how to identify students' WMC from their learning behaviors in learning systems. A general framework for automatically identify WMC from students' behavior in a learning system is introduced in this section. The proposed framework is not restricted to a particular learning system and extends our work on identifying learning styles (Graf et al. 2009a) by additionally considering WMC in the detection process.

The framework consists of two components: the data extraction component and the calculation component, as shown in Fig. 1.1. The data extraction component is responsible for extracting relevant data from the learning system's database, preprocessing these data, and passing the preprocessed data to the calculation component. The calculation component then uses these data to detect patterns from students' behavior (in the Pattern Detector) and calculates students' WMC from the detected patterns (in the WMC Calculator).
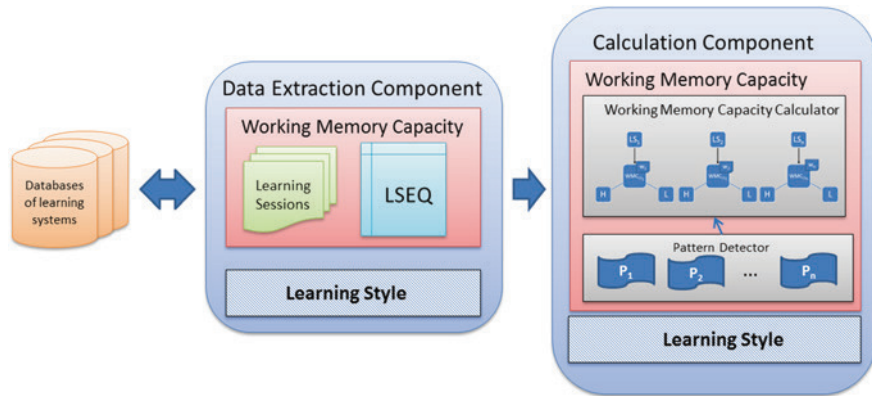
Fig. 1.1 Framework for Identifying WMC

1.2.1 Preprocessing of Data in Data Extraction Component

The detecting tool, DeLeS (Graf et al. 2009a), has been extended in order to identify not only learning styles, but also WMC. In order to analyze students' behavior from the log information in a database of a learning system, some preprocessing of behavior data and course data need to be conducted. The preprocessing includes the following: (1.1) identifying learning sessions, (1.2) filtering out activities that are not dedicated to learning as well as activities where students visit a learning activity only for a very short time, and (1.3) building a learning sequence table called LSEQ table that includes the structure of the course in terms of the predefined sequence of learning activities/objects in a course. The preprocessing of data provides the required input data for the calculation component in order to analyze relevant behaviors for WMC detection. In the next subsections, the three preprocessing steps are described in more detail.

1.2.1.1 Identifying Learning Sessions

A learning session is a series of learning activities that a student does while focusing on learning. A learning session typically starts when a student logs in and ends when a student logs out. Furthermore, we additionally consider breaks in learning or simply closing the learning system without logging out. In order to do so, for each learning activity, an upper threshold is predefined by teachers based on the type of activity to indicate the maximum time a student would typically spend on a learning activity. This threshold is used to identify learning breaks based on log data which typically include timestamps of each activity that a student does. Such learning breaks then indicate the end of one learning session and the beginning of a new learning session.

1.2.1.2 Filtering Learning Activities

When analyzing the behavior patterns of students to infer indications about their WMC, we only focus on learning activities. Therefore, general activities such as a student making modifications to his/her user profile or a user checking his/her marks are not seen as learning activities and are not considered in a learning session. Furthermore, we filter out activities where a learner spent only a very short time (e.g., because he/she clicked on the wrong link or is searching through pages until he/she finds the page that he/she actually wants to read).

1.2.1.3 Building a Learning Sequence Table

We extract the information about the sequence in which the course is laid out and store this information in an internal database table called LSEQ table. When a course designer/teacher makes any changes to the course structure in the learning system, the modification time is stored in the internal database. Once the course designer/teacher uses the DeLeS tool to detect students' WMC, this modification time is used to check whether the LSEQ table needs to be updated before using it to calculate students' WMC.

1.2.2 Analyzing Relevant Behavior Patterns in the Pattern Detector

The pattern detector of the calculation component is responsible for analyzing relevant behavior patterns. Six patterns are considered, which are explained in the subsequent subsections.

1.2.2.1 Linear Navigation Pattern

Linear navigation means that students learn the materials linearly and follow the learning sequence of the course defined by teachers. Huai (2000) performed an experiment to investigate the relationship between WMC, long-term memory, and a serial/holistic learning style. To draw conclusions about the relationship between WMC and a serial/holistic learning style, linear and non-linear navigational behavior of students was investigated. As a result, Huai also found that students with high WMC tend to focus on linear navigation and students with low WMC tend to use non-linear navigation. Accordingly, if such linear navigation is found, it gives an indication for high WMC. Otherwise, if non-linear navigation is found, it gives an indication for low WMC.

1.2.2.2 Constant Reverse Navigation Pattern

Reverse navigation means that a student revisits an already visited learning object (LO). Constant reverse navigation indicates that a student frequently goes back to an already visited LO. This behavior can be explained by the limited capacity of working memory for students with low WMC (Graf et al. 2009b). The process of constant reverse navigation is caused by an insufficient WMC to hold on the materials that have just been visited (Lin et al. 2003). When the learning materials that a student just read on the previous page should be still fresh in his/her working memory, the constant need to navigate backward is a sign of working memory deficiency. The definition of constant reverse navigational behavior is that there are more than two LOs revisited in the same learning session and the navigational relations of these LOs are not defined in the LSEQ table (and therefore not in line with the sequence of LOs in the course structure). For example, consider a navigation sequence of a student's behavior as follows: from LO A, to B, to C, to D, to A, and to C. In this navigation sequence, two LOs A and C are revisited, and consequently constant reverse navigational behavior is detected. If the constant reverse navigational behavior is found, it gives an indication for low WMC. Otherwise, an indication for high WMC is found.

1.2.2.3 Simultaneous Tasks Pattern

The simultaneous tasks pattern is transferred from the ability of attentional control on performing two tasks simultaneously. Previous studies have shown that when performing two tasks simultaneously, low WMC participants were less accurate than participants with high WMC (Engle 2010; Woehrle and Magliano 2012). For identifying this pattern, overlapping navigational behavior is investigated to indicate that a student is trying to perform two tasks, the visiting and evaluation tasks, simultaneously. If a student visits at least one other LO in between LO A (visiting task) and its evaluation *EA* (evaluation task), overlapping navigational behavior is found. In such situation, the student learns LO A first and then learns other LOs before taking the evaluation of LO A. Therefore, he/she needs to remember the concept of LO A in his/her working memory while learning other LOs. If the student then passes the evaluation of LO A, the simultaneous tasks pattern is found, which gives an indication for high WMC. If he/she fails, the non-simultaneous tasks pattern is identified, which gives an indication for low WMC.

1.2.2.4 Recalling Learned Material Pattern

The recalling learned material pattern is transferred from the relationship between WMC and long-term memory. This pattern is similar to the simultaneous tasks pattern, but it is identified within two different learning sessions.

Prior works have argued that the individual's ability to retrieve information from long-term memory is determined by his/her WMC (Unsworth et al. 2012; Engle 2010). As a result, they found that low WMC participants cannot recall as much information from long-term memory as high WMC participants since low WMC individuals do not search the remembered information in their long-term memory as effectively as high WMC individuals. This pattern is found if a student visits LO A in one session but does not perform an evaluation of his/her knowledge on LO A in that session. In a different learning session, the student then does not visit LO A but goes directly to the evaluation of LO *A (EA)*. If the student then passes the evaluation, it means that he/she could recall the previously visited information from LO A from his/her long-term memory and the recalling learned material pattern is found, which gives an indication for high WMC. If he/she fails the evaluation, the non-recalling learned material pattern is identified, which gives an indication for low WMC.

1.2.2.5 Revisiting Passed Learning Object Pattern

As mentioned in the previous sections, several studies have argued that individuals with low WMC cannot recall as much information from long-term memory as individuals with high WMC (Engle 2010; Unsworth et al. 2012). This pattern considers a situation where a student visited LO A and successfully completed its evaluation (EA) in the same session, but then revisits LO A afterward in a different learning session. In such case, the student seems to have problems recalling information from his/her long-term memory and wants to reread some of the already learned information. The more time the student spends on LO A during such revisit, the more problems the student seems to have in recalling the respective information from the long-term memory and therefore, the stronger the indication for low WMC is. On the other hand, if the time the student takes for reading and recalling on LO A is low, an indication for high WMC is given.

1.2.2.6 Learning Style Pattern

The learning style pattern is based on the relationship between learning styles and WMC. Graf et al. (2009b) investigated the direct relationship between WMC and the four learning style dimensions of the Felder-Silverman learning style model (FSLSM) (Felder and Silverman 1988), namely the active/reflective, sensing/intuitive, visual/verbal, and sequential/global dimensions. The results of the study showed that students with a reflective or intuitive learning style tend to have high WMC and students with an active or sensing learning style tend to have low WMC. For the visual/verbal dimension, the study found only a one-directional relationship, namely that learners with a verbal learning style tend to have high WMC, whereas visual learners have either high or

low WMC. No relationship for the sequential/global dimension was found. The learning style pattern considers these relationships. Accordingly, if a student has an active or sensing learning style, this gives an indication for low WMC. On the other hand, a reflective, intuitive, or verbal learning style gives an indication for high WMC. An average value of all indications from a student's learning styles is calculated and this value represents the overall indication of WMC for this learning style pattern.

1.2.3 Calculating Student's WMC in WMC Calculator

After preprocessing the data, these data are used to calculate the students' WMC in the WMC calculator based on the five navigational behavior patterns and the learning style pattern. If a navigational behavior pattern is detected in a relation between two LOs, this relation is considered as an activated relation for the particular pattern. In each learning session, a value p is calculated for each of the five navigational behavior patterns based on the number of activated and non-activated relations in this session. This value p shows how strongly the student's behavior represents the respective pattern. Subsequently, the value p for each pattern is transferred to its indication for WMC (e.g., a high p value for linear navigation provides an indication for high WMC). Then, the indications from the five navigational behavior patterns and the indication based on the learning style pattern are summed up and divided by the number of activated patterns (where the learning style pattern is considered as activated as soon as the learning styles of the student are known). The result of this calculation represents the indication for WMC of the respective learning session. Although the learning style pattern is not dependent on learning sessions, we decided to add the indication from this pattern in each session in order to ensure that this pattern has the same impact in the detection process as all other navigational behavior patterns. Each learning session also contains a weight, which determines the influence of each session on the overall value of WMC and is calculated based on the number of activated relations in a session for all patterns. In order to calculate the student's WMC, the WMC indication of each session is multiplied by the weight of the respective session. Subsequently, the results for all sessions are summed up and divided by the number of sessions. The resulting value is the identified WMC for the respective student.

The DeLeS tool for identifying students' WMC and LS based on their behavior has been implemented as a block plugin into the learning management system Moodle. For the visualization of individual student's WMC, as show in Fig. 1.2, a teacher can select a particular student and can see his/her WMC, which is presented on a scale from 0 to 1, where 0 indicates a very low WMC, and 1 indicates a very high WMC.
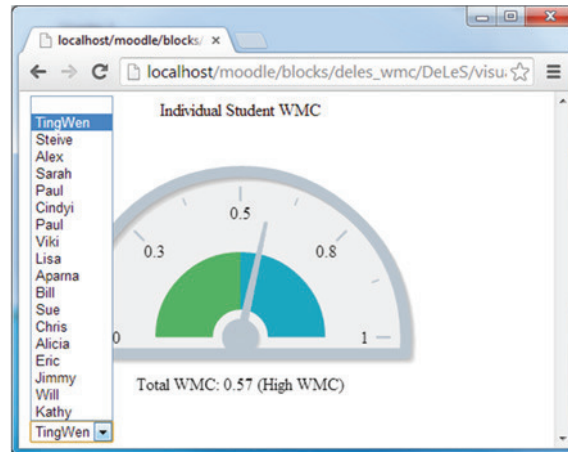
Fig. 1.2 Individual Student WMC

Furthermore, teachers can access more detailed information about students'
WMC with respect to a particular learning session, as shown in Fig. 1.3. A teacher
can see the students' behavior of each learning session based on the six patterns
(LN: Linear Navigation; CR Constant Reverse navigation, ST: Simultaneous
Tasks, RC: ReCalling learned materials, RV: ReVisiting passed learning object,
and LS: Learning Style) and what indication this behavior gives with respect to
a student's WMC. As shown in Fig. 1.3, the blue bars represent indications for
high WMC and the green bars represent indications for low WMC. The WMC of
each session is calculated based on the indications from all patterns. For example,
Fig. 1.3 shows that the respective student performed more linear navigation behav-
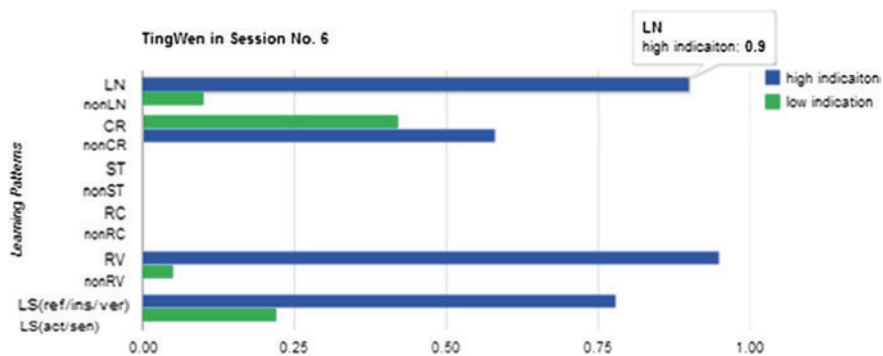ior than non-linear in session 6 and therefore, the LN pattern gives an indication

Fig. 1.3 Interface for showing WMC analyzed results in a particular learning session—LN, CR, ST,
RC, RV represents the activated behaviors of respective patterns; nonLN, nonCR, nonST, nonRC,
nonRV represents the non-activated behaviors of those patterns; LS(ref/ins/ver) represents reflective,
intuitive, and verbal learning styles; LS(act/sen) represents active and sensing learning styles

value of 0.9 on a scale from 0 to 1 where 0 represents a strong indication for low WMC and 1 represents a strong indication for high WMC. Accordingly, the indication value of 0.9 suggests that the student has high WMC.

1.3 Analyzing Course Contents in Learning Management Systems with Respect to Learning Styles

A person's learning style is the method that best allows the person to gather and to understand knowledge in a specific manner. Once a learner's particular learning style is identified, it is possible to identify ways in which the learning process can be improved (Onyejegbu and Asor 2011). On the other hand, making teachers aware of how well their courses fit with diverse learning styles can help them in improving their courses to support students with different learning styles.

Our research utilizes the Felder and Silverman's Learning Style Model (FSLSM) (Felder and Silverman 1988) because of its applicability to e-learning and compatibility to the principles of interactive learning systems design (Kuljis and Liu 2005). In this model, Felder and Silverman proposed four dimensions of learning styles (active/reflective, sensing/intuitive, visual/verbal, and sequential/global) and teaching styles (active/passive, concrete/abstract, visual/verbal, and sequential/global), where each teaching style corresponds to (matches with) a learning style. Many researchers have conducted research to detect the learners' learning styles and provide recommendations and adaptations for online courses based on learning styles (e.g., Paredes and Rodríguez 2004; Graf and Kinshuk 2007). Our research is different from the previous works in that we focus on analyzing existing online courses and making teachers aware of how well those courses fit with diverse learning styles and the current cohort of learners. This section illustrates the design and the implementation of a mechanism for analyzing the course contents, and a visualization tool that shows the support level of the course for diverse learning styles.

1.3.1 Course Analyzing Mechanism

A mechanism for analyzing existing courses in LMSs is proposed in order to infer which learning styles they currently support (El-Bishouty et al. 2012). The mechanism recognizes how well each section of an existing course fits to each of the eight poles of FSLSM (Felder and Silverman 1988) by calculating the average of three factors: the availability, the frequency, and the sequence of the learning objects (LOs) in that section. Consequently, the results can be summarized for each section and for the whole course. The mechanism currently considers eleven types of LOs as follows:

- *Commentaries*: provide learners with a brief overview of the section.
- *Content objects*: are used to present the learning material.
- *Reflection quizzes:* include one or more open-ended questions about the content of a section.
- *Self-assessment tests*: include several close-ended questions about the content of a section.
- *Discussion forum activities*: provide learners with the possibility to ask questions and discuss topics with their peers and instructor.
- *Additional reading materials*: provide learners with additional sources for reading about the content of the section.
- *Animations*: demonstrate the concepts of the course in an animated multimedia format.
- *Exercises:* provide learners with an area where they can practice the learned knowledge.
- *Examples*: illustrate the theoretical concepts in a concrete way.
- *Real-life applications*: demonstrate how the learned material can be related to and applied in real-life situations.
- *Conclusions*: summarize the content learned in a section.

Certain LO types can support diverse learning styles; on the other hand, it is possible that they have no effect. The availability of types of LOs is considered as a factor to infer the learning styles that a section of the course fits well. It measures the existence of LO types in the section that can support each learning style (ls) in respect to all types of LOs that can support that learning style. The availability factor is calculated using formula 1.1. On the other hand, the frequency factor measures the number of LOs in the section that support each learning style in respect to the frequency threshold. The frequency threshold represents the sufficient number of LOs in a section to fully support a particular learning style. This threshold is predefined and can be adjusted by the teacher if needed. If the number of LOs that support a particular ls in a section is less than the value of the frequency threshold, then the frequency factor is obtained by formula 1.2, otherwise the frequency factor takes the value 1, which means a full frequency support level for that learning style. The obtained values for both, the availability factor and the frequency factor, range from 0 to 1, where 1 indicates a strong suitability to the learning style and 0 means no support.

$$Ava_{ls} = \frac{(\# \text{ of existing LO types that support ls})}{(\# \text{ of LO types that support ls})} \qquad (1.1)$$

$$Freq_{ls} = \frac{(\# \text{ of existing LOs that support ls})}{(\text{frequency threshold})} \qquad (1.2)$$

$$Seq_{ls} = \frac{\sum_{i=1}^{n} f_{ls}(LO_i) \times w_i}{\sum_{i=1}^{n} w_i}, \quad 0 < w \leq 1 \qquad (1.3)$$

Actually, not only the types but also the order and the position of the LOs affect the suitability of a course regarding different learning styles. The sequence factor measures the suitability of the sequence of LOs for different learning styles. We calculate the sequence factor for each LO according to its type, location, and order. It is determined according to how much this LO type in that place fits with each of the eight learning styles of FSLSM. The sequence factor for each learning style is calculated using formula 1.3. In this formula, f_{ls} (LO$_i$) = 1, if LO$_i$ is suitable for that learning style at that location, and f_{ls} (LO$_i$) = 0 otherwise. The weight w represents how well the position of a LO fits to the learning style, and n is the number of LOs in the section. Formula 1.3 represented the weighted mean of f_{ls}(LO$_i$). Its value ranges from 0 to 1, where 1 indicates a strong suitability for the learning style and 0 means no support.

1.3.2 System Implementation

Based on the course analyzing mechanism, a tool is implemented for analyzing and visualizing the suitability of a course for students' learning styles (El-Bishouty et al. 2013). It is called interactive course analyzer. By utilizing drag and drop functionality, the tool allows the teacher to play around with the course structure (by adding, moving, and/or removing LOs) showing the expected changes in the course support level for diverse learning styles. The interactive course analyzer aims at helping teachers to improve the support level of their courses by making efficient modifications in the course structure to meet the need of different students' learning styles.

This tool is implemented as a web application. It is mainly developed using MySQL relational database management system and PHP scripting language. It is a stand-alone application that runs on the server side. It connects to a LMS database (Moodle as an example), retrieves the existing course structure and applies the course analyzing mechanism to analyze the course contents with respect to learning styles.

Moreover, the interactive course analyzer visualizes the analysis results and shows how well a course fits with students' learning styles. It provides the teacher with two visualization modes: the General Mode and the Cohort Mode. The General Mode visualizes the support level of a course for diverse learning styles based on FSLSM. The Cohort Mode visualizes the support level of a course in respective to the learning styles of the cohort of students enrolled in that course. Students' learning styles can be calculated through, for example, the ILS questionnaire (Felder and Soloman 1997) or by a tool such as DeLeS (Graf et al. 2009a).

1.3.3 System Usage

There are two methods to access the interactive course analyzer. The first method is embedded into the LMS interface through an add-on that works for a particular LMS (e.g., a block in Moodle), which provides a direct link to the tool interface. This method automatically retrieves the teacher's authentication information from the LMS, and adapts the interface for the teacher's current course and students enrolled in that course. The second method is a standalone web application that requires entering the authentication information manually (such as the user name and password to access the LMS and the internal databases).

Whenever the teacher accesses the tool to analyze a particular course, the interactive course analyzer retrieves the course structure data, analyzes the course based on learning styles, retrieves the learning style data of students enrolled in that course, and then visualizes the course support level. The visualization part of the tool consists of four similar charts that show how well the course and a selected section fit with students' learning styles. Two of the charts visualize the course support level before and after the modifications made by the teacher in the course structure. Similarly, the other two charts show the selected section support level before and after the modifications.

Figure 1.4 illustrates the visualization part of the tool interface for a selected section in General Mode. Each chart consists of two parts. The upper part of a chart consists of a set of bars to show the strength of the harmony of the course/unit/section with each of the eight learning style poles (i.e., active, reflective, visual, verbal, sensing, intuitive, sequential, and global), in terms of percentage (calculated by the average of the three factors illustrated in Sect. 1.3.1). Each learning style dimension is represented by two horizontal bars, one for each pole, where the two poles show the two different preferences of the dimension. The longer the bar, the more the course/unit/section fits with the learning style. The lower part of a chart contains only one bar that shows the overall support level of the course/unit/section for diverse learning styles (calculated by the average of the support level of the eight poles). Once the teacher moves the cursor over any bar, a tooltip appears to display more details about the analysis factors illustrated in Sect. 1.3.1.

Assume that the teacher made a modification in the selected section by adding an "Animation" LO to that section. The existence of an "Animation" LO can support active, sensing, and visual learning styles (Felder and Silverman 1988). After reanalyzing the course considering the teacher's modification and by comparing the two charts in Fig. 1.4, it can be noticed that the section support levels for active, sensing, and visual learning styles were improved (as shown in the right chart by the black arrows). Consequently, the overall section support level for diverse learning styles improved as well (as shown at the bottom of the right chart).
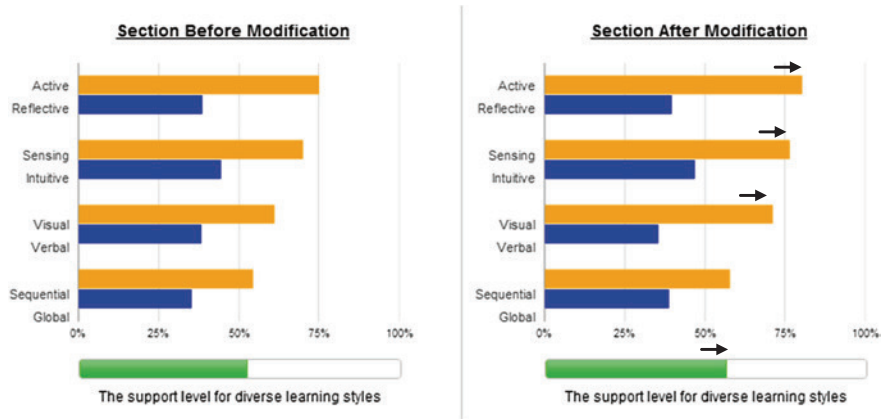
Fig. 1.4 Visualization part of a selected section (general mode)

The teacher can switch to Cohort Mode to visualize the course support level for enrolled students' learning styles. Figure 1.5 illustrates a screenshot of the visualization part of a selected section in Cohort Mode. The charts visualize the data about students' learning styles in comparison with the course support level (calculated by the average of the three factors illustrated in Sect. 1.3.1). As shows in Fig. 1.5, each learning style dimension in a chart contains two bars; the upper one shows the course/section support level for each poles of that dimension (for examples, "active" on the right and "reflective" on the left); the lower bar shows the learning styles of the respective cohort of students, in terms of different levels
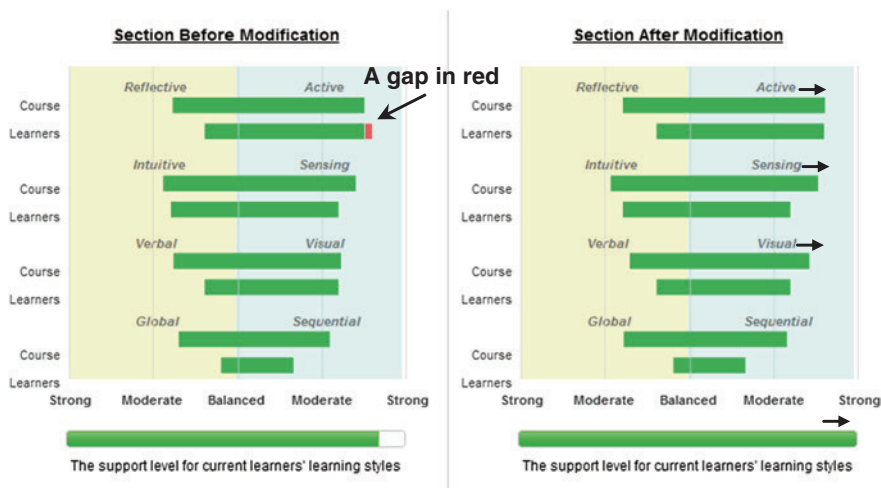

Fig. 1.5 Visualization part of a selected section (cohort mode)

varying from strong to balanced. In case that all students are fully supported, the bar is displayed in green color, otherwise a gap is shown in red. The intensity of the red color indicates the number of unsupported students.

For example, the chart at the left side (Fig. 1.5) shows that reflective, sensing, intuitive, visual, verbal, global, and sequential learners are well supported by the course. On the other hand, active learners are not fully supported; there is a gap between the course support level for the active learning style and the learning style of the respective cohort of students. Once the teacher moves the cursor over any bar, a tooltip appears to display more information about the level of support and the number of supported and unsupported students. Considering the example mentioned in the previous section and the teacher's modification in that example, the chart at the right side (Fig. 1.5) shows that the gap between the course support level and the learning styles of the respective cohort of students was eliminated, and the students were fully supported (as shown at the bottom of the right chart).

The visualization interfaces make teaches aware of how their modifications would impact the course support level for students with different learning styles. Once the required support level is reached, the teachers can navigate to the course webpage in the LMS and actually implement the necessary modifications in the course structure to improve the course support level for better supporting students with different learning styles.

1.4 Automatic Detection and Visualization of Device Functionalities and Usage

While the previous two sections consider analyzing learners' characteristics and courses in LMSs based on learners' cognitive abilities and learning styles, this section focuses on the context of a learner. The context plays a relevant role in ubiquitous and mobile learning environments. The recent advances in mobile technologies have allowed the widespread use of mobile devices around the world. Accordingly, learning can take place anytime and anywhere using mobile devices (e.g., smart phones, tablets) to facilitate human interaction and access to learning contents with fewer restrictions of time and location (Chen et al. 2008).

Mobile learning, as it is known, is a crucial aspect of ubiquitous learning. Such mobile settings bring important improvements for ubiquitous learning by providing a more flexible and authentic experience for the learner. However, additional factors (such as the learner's context) influence the learning process in ubiquitous learning environments and should be considered, especially when aiming at considering adaptation and personalization aspects. We address this issue using data collected from the usage of the learners' mobile devices. The usage of the learner's devices provides important information about the user and his/her context (Ogata et al. 2010). The functionalities (features) of a

device work as sensors gathering different data such as location, ambient light, humidity, temperature, and connectivity. Such data can be used to build a context profile (Roman and Campbell 2002).

Details about the learner context help in the process of personalizing the learning experience. Furthermore, the way the learner uses the device—its applications and features—is a good indicator about his/her preferences and other personal traits (information to build a user profile). The user profile and the context profile are elements which compound a comprehensive model about the learner and his/her context that can be considered as the basis of a personalized adaptive learning system (El-Bishouty et al. 2007; Graf and Tortorella 2012).

Several applications are developed in order to monitor the usage of smart mobile devices aiming at enchanting the device usage. Due to the advantages of open source, many of them are implemented for Android-powered mobile devices (Joiku Phone Usage 2013; Elixir 2012). In contrast to such applications, the proposed framework in this section illustrates a methodology to automatically detect the existence of types of device features and functionalities that the learner may use in his/her device for learning. It is not targeting a particular feature, or a certain device type or operation system. In addition, it monitors how the learner interacts with and uses each feature in order to understand and recognize the learner's preferences on how to use mobile devices for learning. Such context information opens up new possibilities for providing adaptive learning environment.

1.4.1 Framework Architecture

The proposed framework (Fig. 1.6) is a client–server generic framework designed to run on smart phones, tablets, laptops, and desktop computers (Lima et al. 2013). On the client side—running on the learners' devices—the application is divided into two parts. The first one is the User Part, where personal information about the user (i.e., learner) is gathered and usage data visualization is presented. This part has two components: the Personal Information Manager, allowing the learner to login and to provide personal information (e.g., login name, full name, email address, and other characteristics). This information is grouped under the name of User Object. The second component is the Visualizer, which is responsible for providing a user interface to show the feature availability and usage information.

The second part of the application is the Device Part, where device information about the availability and usage of features is collected. This is done by Feature Detectors and the Tracker. Each Feature Detector is associated with a feature (e.g., internet connection types, keyboard presence, and available touch screen) and able to discover whether the respective feature is available in that device. The data collection from all Feature Detectors is used to create the Device Object, which includes information to describe the tracked device in terms of its features. Furthermore, the Feature Detectors provide information about the usage of the respective features to the Tracker.
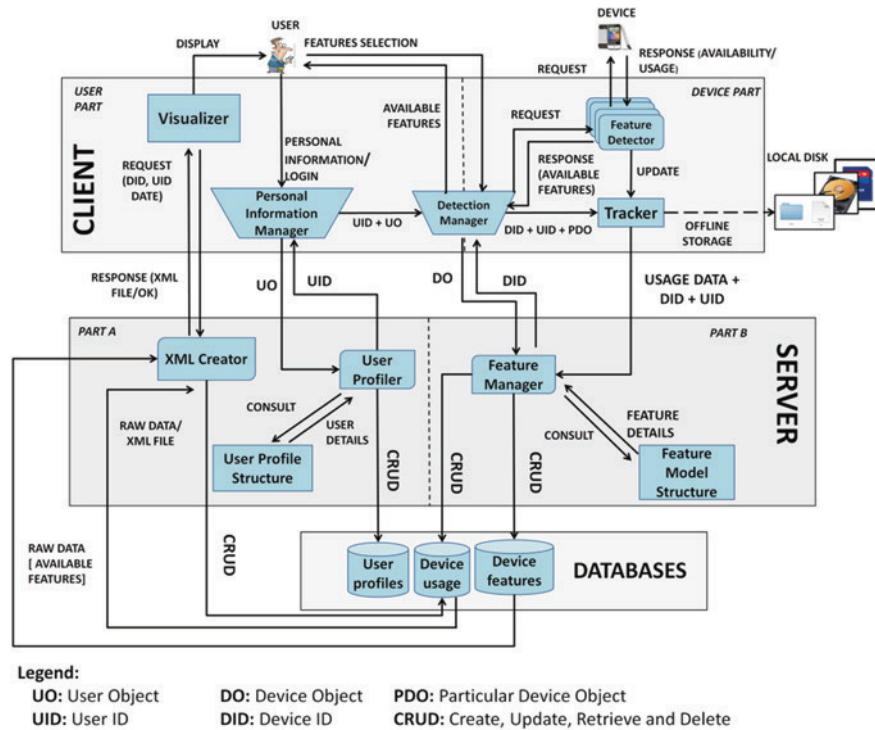
Fig. 1.6 The framework architecture

The Tracker gathers the learner's device usage data by receiving updates from the Feature Detectors and stores this information on the server. However, if there is no connection to the server available, the Tracker creates a local backup file with the gathered data and postpones the online storage until connection to the server is available. Moreover, there is a component which belongs to both parts of the client side, the Detection Manager. The Detection Manager allows the learner to select what features the system should track. In order to do so, the Detection Manager detects what features are available in the device by calling the Feature Detectors when the learner starts the application for the first time and displays these features for selection. The set of information about the features selected by the learner is grouped under the name of Particular Device Object and represents a subset of the information in the Device Object. Furthermore, the Detection Manager encapsulates the user id, the device id, and the Particular Device Object and sends all this information to the Tracker.

The server side mainly manages the database and the identification of devices and users, and is divided into two parts. Part A communicates with the User Part of the client and consists of the following components: the User Profiler, which is responsible for receiving the user information as a User Object from the client and

for storing it in the database. The second component is the User Profile Structure, which stores what personal information of the learner is considered in the framework; and the third component is the XML Creator which processes the availability and usage data and generates a XML file which is used by the Visualizer.

Part B of the server side is responsible for the communication with the Device Part of the client. It is composed of the Feature Manager and the Feature Model Structure. The former is responsible for receiving the device information in form of a Device Object, including the available features on the device and its usage data from the client, and for storing this information in the database. The Feature Model Structure describes the device features considered in the system. Moreover, there is a database, divided into three parts: First, it stores the device information, including the device id and which features are available to be used. In other words, it stores a set of Device Objects. Second, it stores user information (e.g., login name, full name, email address, and other characteristics), in other words, a set of User Objects. Third, it combines the data relating a device to a learner and stores the usage data of the device by the learner.

1.4.2 Application for Android Phones

As mentioned above, the proposed framework is designed for tracking and analyzing the availability and usage of device features from different devices such as mobile phones, tablets, and desktop computers. In this section, we describe an application for mobile phones, running on the Android operation system.

This application—the Usage Observer—aims at providing the possibility for learners to select features on their devices, monitor the usage of those features, and view data about feature availability and usage in a user-friendly way. Moreover, learners can allow teachers to access these data. The application is composed of seven interfaces: login, main, feature selection, personal information/preferences, tracker management, feature usage visualization, and administration. Some of the major interfaces can be seen in Figs. 1.7 and 1.8.

The login and registration process is managed by the Personal Information Manager and the Detection Manager. If the learner does not have an account yet, he/she needs to go through the registration process. In the first step, the learner can provide personal information and preferences (as shown in Fig. 1.7b), leading to the creation of a User Object by the Personal Information Manager. This interface (as well as the other user interfaces) is implemented as an Android component extension called Activity.

In the second step of the registration process, the learner registers his/her device by accessing the Detection Manager, where he/she can select which features should be tracked (Fig. 1.8a). This interface presents the device's available features, identified by the Feature Detectors, and allows the learner to select which features he/she wants to be tracked. As a result, a Particular Device Object is created containing information on those selected features. The Feature Detectors
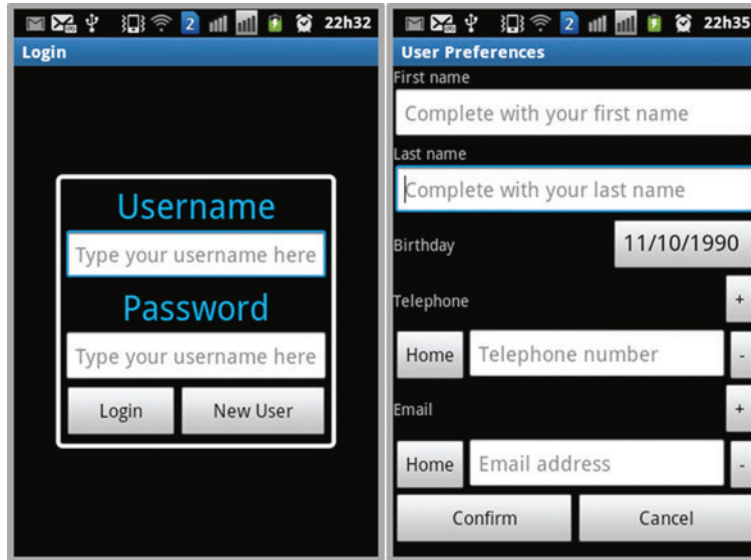
Fig. 1.7 Application interfaces—**a** login interface; **b** personal information interface
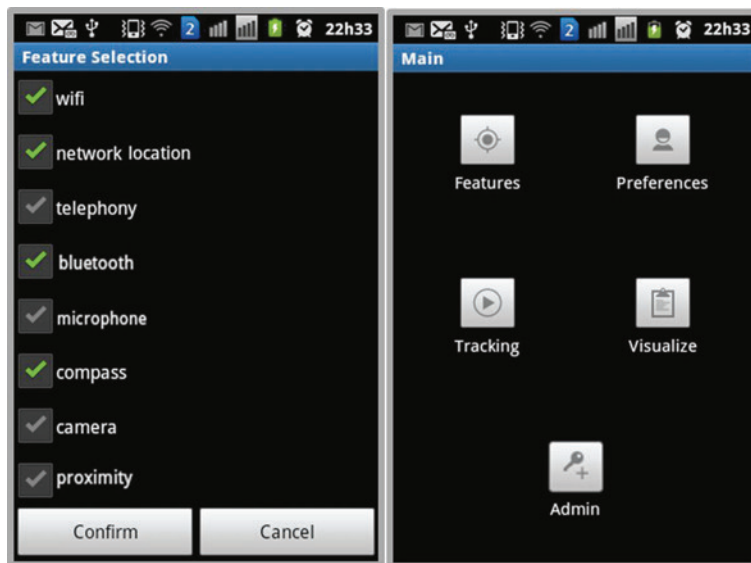

Fig. 1.8 Application interfaces—**a** Feature selection interface; **b** Main interface (access point of the other interfaces)

are implemented as one single service, called Detection Service. Services are an Android component extension, which run in the background and typically perform long-term tasks. If a learner is using different devices, the registration for the user account has to be done only once but whenever the learner using a new device, this device has to be registered by performing the second step of the registration process. Once the learner and his/her device are registered, he/she can login by providing the correct username and password (Fig. 1.7a) and is presented with the main interface (Fig. 1.8b), where he/she can navigate through the application.

The main interface allows the learner to access the personal information entered in the registration process (through the Preferences symbol) and the feature selection interface (through the Features symbol) in order to change personal information and selected features. Furthermore, the main interface provides access to the tracking and visualization interfaces. The tracking interface presents raw data about the tracked features (accessible through the Tracking symbol) and the visualization interface shows user-friendly visualizations about the availability and usage of features on the learner's devices (accessible through the Visualize symbol). Administrators and teachers can additionally access the administrator interface (through the Admin symbol), which provides them with additional visualization interfaces to compare usage information from different learners and/or different devices.

While learners are using their devices, the system tracks the usage of the selected features. This is done by the Tracker Service, which represents part of the Feature Detectors and part of the Tracker component in the framework. The Tracking Service is responsible for collecting data about the usage of the previously selected features. One of the biggest development challenges was to implement the algorithm for the Tracking Service to track the usage of the selected features. The Android platform does not provide any direct way of collecting this type of data for certain features. After evaluating several different approaches, we implemented this service by reading the system generated logs and gathering the timestamps related to the use of each selected feature. Hence, the Tracker component in the framework works as a logger which means the developed Tracker service collects log data provided by the system and sends it to the framework's server side. The server is then responsible for parsing the received log data and for obtaining the selected feature's usage data and statistics based on the timestamps contained in the log data. This task is performed by the Feature Manager component, which then stores the new information in the database.

1.5 Conclusions

This chapter illustrated three different approaches to automatically analyze learners' characteristics and courses, building a foundation for providing learners with adaptive and personalized support based on their cognitive abilities, learning styles, and context.

A framework is proposed for identifying students' WMC from their activity log information in learning systems, as well as its implementation into the detection tool DeLeS. Six behavior patterns have been identified to be, on one hand, relevant for the identification of WMC as concluded by the literature, and on the other hand, to be domain and learning system independent so that our proposed approach is generic and can be used in different learning systems. By knowing students' WMC in learning systems, teachers can individually support students and provide them with personalized recommendations, while students can better understand their weaknesses and strengths, and use this information to improve their learning. Furthermore, information about students' WMC can be used as input for an adaptive learning system to automatically provide students with individualized materials and activities as well as personalized recommendations, considering their WMC.

With respect to learning styles, a mechanism and an interactive tool are presented for analyzing existing course contents in LMSs based on students' learning styles. The tool provides teachers with an interactive graphical user interface that allows them to play around with the course structure. This interactive interface supplies the teachers with drag and drop utility to add, move, and/or remove LOs, and then visualizes the changes in the course support level. This supports the teachers to decide which modifications should be implemented in the actual course structure. The aim of these modifications was to meet the need of different students' learning styles, which enables the teachers to provide personalized support to meet the need of students with different learning styles.

For the identification of context, a framework and an application are presented for identifying learners' preferences on how to use their devices for learning. This approach aims at building a comprehensive context profile through detecting available features of a device (e.g., keyboard, touch screen, internet connection, camera, GPS, and so on) and tracking the usage of these features by its users. Furthermore, the application visualizes the gathered data in a user-friendly way. The gathered information is the basis for extending learning systems with advanced adaptive and intelligent capabilities that allow personalizing user interfaces and providing learners with adaptive course structures and recommendations based on availability and previous usage of device features.

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