AN ARCHITECTURE FOR DYNAMIC STUDENT MODELLING OF LEARNING STYLES IN LEARNING SYSTEMS AND ITS APPLICATION FOR ADAPTIVITY*

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ABSTRACT

Considering students' learning styles in education and especially in technology enhanced education can have many benefits for students such as providing them with personalized recommendations and advice based on their learning styles. However, in order to provide students with such personalized recommendations and advice, their learning styles have to be identified first. In this paper, we introduce an architecture that aims at monitoring students' behaviour in online courses and using this information in order to build and frequently update a cognitive profile that consists of information about students' learning styles. Dynamic student modelling enables systems to incrementally learn students' learning styles, identify and consider exceptional behaviour of students, and update students' learning styles once they change over time. In order to quickly initialise the cognitive profile, the architecture additionally provides a learning style questionnaire that can (but does not have to) be used by students and therefore combines static and dynamic student modelling of learning styles. The proposed architecture can be easily integrated in different learning systems, requiring only few adjustments with respect to locating data about students' behaviour, providing notifications about students' actions in a course, and presenting a link to the learning style questionnaire. The architecture has been integrated in a learning system and an adaptivity module has been developed to demonstrate the benefits of dynamic student modelling. This adaptivity module extends the proposed architecture by accessing the information about students' learning styles in the cognitive profile and using this information for providing students with adaptive feedback about their learning styles and how to improve their learning processes considering their learning styles.

KEYWORDS

Dynamic Student Modelling, Static Student Modelling, Learning Styles, Adaptivity and Personalization

1. INTRODUCTION

Knowing students' learning styles and considering this information in the learning process can lead to many benefits for learners. First, students can be made aware of their learning styles as well as the implications of their learning styles for learning, helping them to understand why learning is sometimes difficult for them and building the basis for developing their weaknesses. Second, the information about students' learning styles can be used to provide students with learning material/activities and personalized recommendations that fit their learning styles. Such adaptivity has high potential to make learning easier and faster for students, as demonstrated by studies such as those by Bajraktarevic et al. (2003) and Graf and Kinshuk (2007).

To consider learning styles in education, students' learning styles need to be known first. Brusilovsky (1996) distinguished between two ways of student modelling. In the *collaborative* approach, the students provide explicit feedback which can be used to build and update a student model, such as filling out a learning style questionnaire. In the *automatic* approach, the process of building and updating the student model is done automatically based on the behaviour of students while they are using the system for learning. The automatic approach is direct and free from the problem of inaccurate self-conceptions of students. Moreover, it allows students to focus only on learning rather than additionally providing explicit feedback about their preferences. In contrast to learning style questionnaires, an automatic approach can also be more

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accurate and less error-prone since it analyses data from a time span rather than data which are gathered at one specific point of time.

Additionally, student modelling can be classified as *static* or *dynamic*. Static student modelling refers to an approach where the student model is initialised only once (mostly when students register in the system). In contrast, a dynamic student modelling approach frequently updates the information in the student model and therefore allows responding to changes of the investigated student characteristic. A dynamic approach has two advantages over a static one in the context of identifying learning styles. First, dynamic student modelling can consider exceptional behaviour of students and can extend static student modelling by incrementally improving and fine-tuning the information in the student model in real-time. Second, since many of the major learning style models argue that learning styles can change over time, dynamic student modelling allows to consider such changes and update the learning styles once they changed.

A lot of adaptive learning systems that are based on learning style adaptation use questionnaires (a static and collaborative approach). Examples of such systems are CS383 (Carver et al., 1999), IDEAL (Shang et al., 2001), and LSAS (Bajraktarevic et al., 2003). Recently, more and more research has been done on developing automatic student modelling approaches by considering students' behaviour in a course. However, these approaches typically use a predefined amount of behaviour data for identifying students' learning styles at one point of time and are therefore still static approaches (Cha et al., 2006, Graf et al., 2009, García et al., 2007). Very little research has been conducted on dynamic and automatic student modelling of learning styles so far, where the system monitors a students' behaviour and uses this behaviour data to frequently update learning styles of students.

In this paper, an architecture is introduced which integrates dynamic student modelling into existing learning systems, enabling them to monitor students' behaviour, analyse these data for detecting and frequently updating students' learning styles, and storing the information about students' learning styles in a student model which can be accessed by the system in order to provide adaptive and personalized support for students. The introduced architecture has been integrated in a learning system and a module for providing students with adaptive support has been developed in order to demonstrate the benefits of dynamic student modelling of learning styles and the introduced architecture.

This research is based on the Felder-Silverman learning style model (FSLSM) (Felder and Silverman, 1988) which assumes that each learner has a preference on each of its four dimensions: active/reflective, sensing/intuitive, visual/verbal, and sequential/global. Accordingly, FSLSM is a learning style model that describes learning styles in detail and is therefore highly appropriate for providing adaptivity in learning systems (Kuljis and Liu, 2005, Carver et al., 1999). For that reason, it is very often used in technology enhanced learning. FSLSM is based on the concept of tendencies, allowing handling of exceptional behaviour by considering learning styles as a main tendency rather than as an obligatory type. Furthermore, FSLSM assumes that these tendencies are more or less stable but can change over time, and that they are domain independent.

In the next section, the architecture for dynamic student modelling is described. Section 3 deals with the integration of the architecture into a learning system and describes the developed adaptivity module. Section 4 concludes the paper and provides some directions for future work.

2. ARCHITECTURE FOR DYNAMIC STUDENT MODELLING

In this section, an architecture is presented that aims at enabling existing learning systems to build and frequently update a cognitive profile of their students, which is stored in a student model and includes information about students' learning styles based on FSLSM. The architecture is illustrated in Figure 1.

The modules are designed to be as independent as possible with respect to the learning system, so that they can be integrated in different systems. The only exception is the *Data Extraction Module* which has to extract relevant data from the data sources of the learning system (e.g., a database that includes logs of students' behaviour) and is therefore system-dependent. Furthermore, the *Notification Mechanism* has to be directly integrated in the learning system for sending notifications whenever a student performs an action in the learning system. In addition, a link to the *Static Student Modelling Module* has to be provided within the learning system for integrating static student modelling.

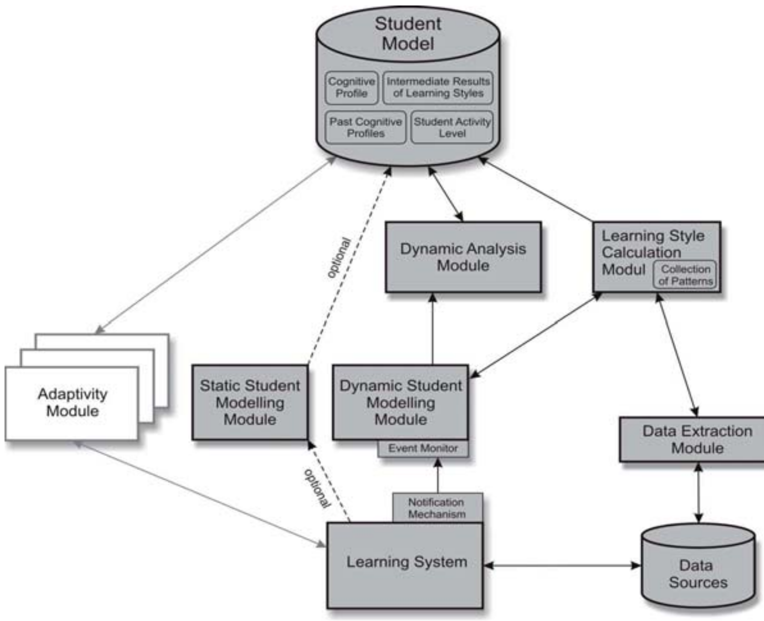

Figure 1. Architecture for dynamic student modelling

To use the information about learning styles identified through the proposed architecture for dynamic student modelling, adaptivity modules can be added to the learning system. These adaptivity modules can access the cognitive profile in the *Student Model* and use the information about students' learning styles, for example, for providing students with personalized recommendations and/or adaptive courses based on students' learning styles. The implementation of such an adaptivity module is described in Section 3.

In the following subsections, the modules of the architecture are described in more detail.

2.1 Static Student Modelling Module

The *Static Student Modelling Module* aims at providing an option for initialising the cognitive profile through the use of a questionnaire. Such a questionnaire enables a system to quickly gather information about students' learning styles, which can then be refined and updated through dynamic student modelling once students use the system for learning. Therefore, by combining static and dynamic student modelling, adaptivity can be provided right after a student filled out the questionnaire rather than having to wait until enough information from student's behaviour is available for calculating his/her learning styles.

The *Static Student Modelling Module* is called through a link that can be added in the learning system, for example, when students register in the system. Once students click on this link, the *Static Student Modelling Module* presents them with the Index of Learning Styles questionnaire (Felder and Soloman, 1997), a 44-item questionnaire that has been developed by Felder and Soloman in order to identify learning styles based on FSLSM. Once students filled out this questionnaire, the results, four values between +11 and -11 indicating the preference on each of the four learning style dimensions of FSLSM, are normalised to values between 0 and 1 and stored in the cognitive profile of the *Student Model.* These values are used as currently identified learning styles which are later refined and updated through dynamic student modelling. Students can choose not to fill out the questionnaire. In that case, no information is stored in the cognitive profile and dynamic student modelling is used to build and update information about students' learning styles from students' behaviour in the learning system.

2.2 Notification Mechanism

The *Notification Mechanism* is a system-dependent component which is integrated in the learning system and can be seen as the interface between the learning system and the *Dynamic Student Modelling Module*. The *Notification Mechanism* is responsible for notifying the *Dynamic Student Modelling Module* when a student is performing an action in the learning system. Actions are defined as visits of learning objects/activities. Whenever such an action occurs, the *Notification Mechanism* sends a message with the student ID and the course ID to the *Dynamic Student Modelling Module*.

2.3 Dynamic Student Modelling Module

The *Dynamic Student Modelling Module* is responsible for managing the dynamic student modelling process. This includes two activities. First, the *Dynamic Student Modelling Module* monitors students' activity levels, in terms of how many actions they perform, based on the messages received from the *Notification Mechanism*. Second, the *Dynamic Student Modelling Module* requests recalculations of students' learning styles once a student performed a predefined number of actions since the last recalculation of his/her learning styles. Such recalculations aim at considering students' recent behaviour in the calculation process of their learning styles and checking whether their behaviour still reflects the students' learning styles as stored in the cognitive profile of the *Student Model* or updates in the cognitive profile are required. Therefore, the *Dynamic Student Modelling Module* first requests a recalculation from the *Learning Style Calculation Module* and subsequently requests the *Dynamic Analysis Module* to check whether updates are required.

2.4 Learning Style Calculation Module

The *Learning Style Calculation Module* aims at calculating students' learning styles from their behaviour in a learning system. This calculation is based on certain patterns of behaviour, which provide indications of students' learning styles. Such patterns can be, for example, the number of visits of particular types of learning objects/activities such as content, exercises and quizzes, and the time spent on such types of learning objects/activities.

The *Learning Style Calculation Module* includes a collection of patterns, where each pattern provides indications for identifying learning styles based on a particular learning style dimension of FSLSM. Furthermore, information for each pattern is included that states how the pattern affects a certain learning style dimension (e.g., whether a high number of visits of exercises is an indication for an active or reflective learning style). Since different learning systems support different types of learning objects/activities, not all patterns can be used for each learning system and only the patterns that deal with types of learning objects/activities that are considered in the respective learning system are used in the calculation process. The collection of patterns can be extended in the case that a learning system considers types of learning objects/activities that are not included so far.

In order to get data about a student's behaviour with respect to each pattern that is considered in the learning system, the *Learning Style Calculation Module* sends a request to the *Data Extraction Module*, which then returns raw data for each available pattern. These raw data (e.g., the amount of times a student visited a certain type of learning object or the number of minutes a student spent on average on certain types of learning objects) are then transformed to ordered data based on predefined thresholds from literature. Ordered data are used to indicate whether the occurrence of a particular behaviour pattern is high, medium or low (or information about this pattern is not available). Subsequently, these ordered data are related to how the pattern affects a student's learning style by using four values: 3 indicates that the student's behaviour gives a strong indication for the respective learning style, 2 indicates that the student's behaviour is average and therefore does not provide a specific hint, 1 indicates that the student's behaviour is in disagreement with the respective learning style, and 0 indicates that no information about the student's behaviour is available.

By summing up these values for each pattern that is relevant for a particular learning style dimension and dividing these values by the number of patterns that include available information for that dimension, a measure for the respective learning style dimension is calculated. This measure is then normalised on a range from 0 to 1, where 1 represents one pole of the dimension (e.g., active) and 0 represents the other pole of the dimension (e.g., reflective).

This calculation process is very similar to how learning styles are calculated in the learning style questionnaire but uses information from students' behaviour instead of asking students explicitly about their preferences. The approach has been introduced and successfully evaluated by Graf et al. (2009), using a predefined set of patterns for detecting learning styles in learning management systems.

The results of the *Learning Style Calculation Module* are four values between 0 and 1, each value representing the calculated learning style on each of the four dimension of FSLSM. These results are stored in the *Student Model* as intermediate results, representing the students' current learning styles identified at one particular point of time from their behaviour while learning in the system. In the subsequent sections, these values will be referred as *ls_behaviour*. After the calculation and storage of these values is completed, the *Learning Style Calculation Module* notifies the *Dynamic Student Modelling Module*.

2.5 Data Extraction Module

The *Data Extraction Module* connects to the learning systems' database (or other sources of log data) and extracts data of available patterns in the learning system. Since the data extraction is dependent on where particular data are located, this module is system-dependent and has to be adjusted to each learning system that integrates the introduced architecture.

Once the *Data Extraction Module* receives a request from the *Learning Style Calculation Module* to collect data from a particular student, it extracts and returns the data of the available patterns to the *Learning Style Calculation Module*.

2.6 Dynamic Analysis Module

This module is responsible for analysing how the learning styles calculated from students' recent behaviour by the *Learning Style Calculation Module* change over time and whether these changes should lead to a change in the learning styles stored in the students' cognitive profiles. For deciding whether such a revision should be done, two partially conflicting objectives have to be reached. On one hand, the currently stored information in the cognitive profile should reflect the current learning styles of students as good as possible and therefore should be updated as soon as a revision can be done. On the other hand, deviations of students' behaviour have to be considered and the student modelling approach should avoid situations where the learning styles of students are revised and then briefly afterwards this revision has to be reversed.

The *Dynamic Analysis Module* integrates an approach that has been introduced and evaluated by Graf and Kinshuk (2009). This approach uses the intermediate results (*ls_behaviour*) identified by the *Learning Style Calculation Module* as input data, representing the students' learning styles over time calculated based on their behaviour. In order to decide whether a learning style stored in the cognitive profile needs to be updated, three conditions have been formulated that have to be fulfilled. The first condition aims at updating students' learning styles as soon as a change in students' behaviour is noticed and therefore compares the currently stored learning style in the cognitive profile and the mean value of the last *A* identified learning styles (ls_behaviour), where an experiment by Graf and Kinshuk (2009) identified that 3 is a suitable number for *A*. The second and third condition focuses on detecting and considering deviations in terms of exceptional behaviour of students. The second condition looks into the difference between the currently identified learning style ($ls\_behaviour_t$) and the previously identified learning style ($ls\_behaviour_{t-1}$) in order to detect exceptional behaviour. Once exceptional behaviour has been detected, the third condition investigates whether the next identified learning style goes significantly towards the learning style stored in the cognitive profile or shows again exceptional behaviour (which then can indicate a change in a student's learning style rather than exceptional behaviour). If all conditions point to a change in the student's learning style rather than exceptional behaviour, the stored learning style in the cognitive profile is updated by the mean value of the past *A* identified learning styles.

2.7 Student Model

The *Student Model* aims at storing several types of information about students. First, it stores the cognitive profile of students, which includes the four values of students' learning styles based on the four dimensions of FSLSM. This information can be used by adaptivity modules, which can access the students' cognitive profiles and use the information in these profiles, for example, to provide students' with adaptive courses and/or recommendations.

Besides the cognitive profile, the *Student Model* also stores data about students' activity level, past data from the cognitive profile, intermediate results from the *Static Student Modelling Module* including data from the questionnaire, and intermediate results from the *Learning Style Calculation Module* which represent the identified learning styles over time based on students' behaviour.

3. APPLICATION OF THE ARCHITECTURE IN A LEARNING SYSTEM

The above described architecture has been implemented for an online learning system. A *Notification Mechanism* has been integrated in the learning system and the *Data Extraction Module* has been adjusted to the learning system's data sources and the available patterns that can be extracted in the learning system. Furthermore, an *Adaptivity Module* has been developed that uses the information from the cognitive profile in order to make students aware of their learning styles as well as provide them with personalized suggestions on how to improve their learning based on the elements available in their courses.

In the following subsection, the types of courses and course elements of the learning system are described. The next subsection describes how the information in the cognitive profile is used to provide students with adaptive feedback.

3.1 Course Structure and Available Behaviour Patterns

The learning system includes two types of courses: courses that focus on assessment only and courses that focus on learning and assessment. The assessment-only courses consist of exercises, quizzes and a study guide. *Exercises* are mainly for practicing the learned material through theoretical or practical questions which are randomly composed and can therefore be used by the students as often as they want to practice. An exercise can consist of multiple parts where each part includes a question. After a student answered the question, his/her answer is automatically marked and feedback about the correct answer is provided. *Quizzes* are more comprehensive tasks which are intended to be solved by students at the end of a section or course. Students are usually given a certain time limit (e.g., 60 minutes) for solving all the theoretical and practical questions within the quiz. Once a student submitted the quiz, his/her answers are automatically marked and feedback about the correct answers is provided. The *study guide* is a page that includes information about a student's progress in the context of all the concepts of the course.

The courses for learning and assessment also include exercises, quizzes and a study guide but they additionally use elements for presenting learning material. Therefore, each course has chapters, and each chapter consist of sections. Each chapter and section includes an *outline*, which consists of a short introduction, and chapter outlines additionally include a description of the learning objectives. Each section has a *lesson* which consists of several *pages of learning material*, *applied self-assessment questions* which are very practical oriented questions that allow students to apply the learned knowledge in practise, and *theoretical self-assessment questions* which are theoretical questions about the learned material. Furthermore, a section can include *activity-related questions* which facilitate experimentation by providing immediate feedback even to parts of students' answers. In addition, a section can have a *case study* which is a large practical problem with several steps to solve.

Table 1 provides an overview of the considered patterns based on the course elements mentioned above. The last three columns indicate which learning style is related with a high occurrence of the respective pattern. The patterns and their indications are based on the learning style literature (Felder and Silverman, 1988) as well as on the literature about detecting learning styles from behaviour patterns (Graf et al., 2009).

The patterns in Table 1 were considered in the collection of patterns in the *Learning Style Calculation Module* and the *Data Extraction Module* was built based on those patterns.

3.2 Providing Adaptive Feedback based on Learning Styles

The purpose of student modelling is to identify and frequently update information about students which can then be used to provide students with personalized courses and/or recommendations. Therefore, the introduced architecture is intended to be combined with *Adaptivity Modules* which access the student model, retrieve students' learning styles and use the information about students' learning styles to provide students with adaptivity. Such modules have strong interdependences with the learning system since they have to

Table 1. Considered patterns of behaviour from course elements of the learning system
(* marks patterns which are related to parameters such as overall number of actions, solved questions etc.)

Pattern name	Description of patterns	act/ref	sen/int	seq/glo
exercise_stay	avg. time spent on solving an exercise question	ref	sen	
exercise_visits	avg. number of attempts to solve an exercise question	act		
exercise_performance_increase	avg. rate of grade increase on exercise questions	ref	sen	
exercise_performance	avg. final grade on exercise questions		sen	
exercise_stay_results	avg. amout of time spent for studying the feedback of exercise questions	ref	sen	
exercise_sequence_skip	number of time of skipping an exercise question*			glo
exercise_sequence_back	number of times of going back to a previous exercise question*			glo
quiz_sequence_revise	number of times of re-entering a quiz*		sen	
quiz_stay	percentage of time took on avg. for submitting a quiz		sen	
quiz_stay_results	avg. amount of time for studying the feedback of a quiz	ref	sen	
studyguide_visits	number of visits of the study guide*			glo
outline_visit	number of visits of outlines*			glo
outline_stay	avg. amount of time spent on outlines	ref		glo
content_visit	number of visits on content pages*	ref		glo
content_stay	avg. amount of time spent on content pages	ref		
content_back	number of times of re-visiting a content page*			glo
content_skip	number of times for skipping content pages*			glo
asa_solution_visit	number of visits of solutions of applied self-assessment questions*		sen	
asa_solution_stay	avg. amount of time spent on solutions of applied self-assessment questions	ref	sen	
tsa _solution_visit	number of visits of solutions of theoretical self-assessment questions*		sen	
tsa _solution_stay	avg. amount of time spent on solutions of theoretical self-assessment questions	ref	sen	
tsa_solution_back	number of re-visits of a solution in the same theoretical self-assessment page*		sen	glo
activityquestions_visit	number of visits of activity pages*	act	sen	
activityquestions_instances	avg. number of attempts tried for each activity page	act	sen	
activityquesitons_stay	avg. amount of time spent on an attempt of activity-related question	ref	sen	
casestudy_visit_same	avg. number of visits of a case study question	act		
casestudy_visit_diff	percentage of solved case study questions		sen	seq
casestudy _stay	avg. amount of time spent on a case study question	ref	sen	

consider the characteristics of a course, such as the available types of learning objects/activities, in order to provide students with adaptive courses and/or recommendations.

An *Adaptivity Module* has been developed that aims at providing students with adaptive feedback based on their learning styles. This feedback is shown within the *study guide* and consists of three parts. First, students are presented with their learning styles on each of the four dimensions of FSLSM, as they have been identified through static and dynamic student modelling. A five-item scale is used for each learning style dimension, distinguishing for example between a strong active, moderate active, balanced, moderate reflective and strong reflective learning style. Second, each of the learning styles of a student (i.e., active or reflective; sensing or intuitive, etc.) is explained in more detail, pointing out typical characteristics, strengths and weaknesses of students with the respective learning style in a general learning context. Third, students are provided with personalized learning advices, dealing with suggestions on how to learn more effectively based on their individual learning styles and considering the types of learning objects available in the student's course, distinguishing between assessment-only courses and courses that focus on learning and assessment.

4. DISCUSSION AND CONCLUSIONS

This paper introduced an architecture for dynamic student modelling of learning styles based on the Felder-Silverman learning style model, aiming at building and frequently updating a cognitive profile of students' learning styles based on students' behaviour in an online course. For a faster initialisation of the cognitive profile, a static student modelling approach in form of a learning style questionnaire has been added to the architecture which can be used by students optionally.

The architecture is developed in a generic way so that it can be integrated into different learning systems. Only two of the modules in the architecture require modifications if integrated in different learning system. These two modules are the *Notification Mechanism* which sends notifications to the dynamic student modelling approach once a student conducts an action in the learning system as well as the *Data Extraction Module* which requires information on how and where data are stored in the learning system. Furthermore, adaptivity modules can be added to the architecture which aim at providing adaptivity and personalization in the learning system based on the identified learning styles of students.

The application of the introduced architecture has been demonstrated for an online learning system, considering the different types of courses and types of learning objects/activities within this system. Furthermore, an *Adaptivity Module* has been developed which presents students with adaptive feedback based on their learning styles.

Adding dynamic student modelling of learning styles to learning systems has two advantages over using a static approach: (1) it enables the system to incrementally learn students' learning styles and identifies exceptional behaviour of students which can be excluded from the updating process, and (2) it makes it possible to identify changes in students' learning styles over time and updating the cognitive profile respectively. Both advantages lead to more accurate information about students' learning styles and therefore facilitate more effective adaptivity in learning systems. By developing an architecture that can be easily used by different learning systems with few adjustments to the respective systems, dynamic student modelling can enable these systems to provide adaptivity based on students' learning styles, for which benefits such as less study time to achieve on average same grades (e.g., Graf and Kinshuk, 2007) and higher student satisfaction (Popescu, 2008) have been demonstrated.

Future work will deal with developing and providing additional adaptivity modules for the online learning system described in this paper, such as automatically modifying courses, learning objects, and/or learning activities in order to make them fit to students' learning styles. Furthermore, the collection of patterns is planned to be extended (e.g., with patterns about students' navigational behaviour in a learning system as well as with patterns related to additional types of learning objects/activities) and the application of the architecture to other learning systems such as learning management systems is planned. In addition, a qualitative evaluation is planned in order to investigate students' satisfaction with the provided adaptivity.

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