Enriching Intelligent Textbooks with Interactivity: When Smart Content Allocation Goes Wrong

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Abstract. One of the main directions of increasing the educational value of a digital textbook is its enrichment with interactive content. Such content can come from outside the textbooks - from multiple existing repositories of educational resources. However, finding the right place for such external resources is not always a trivial task. There exist multiple sources of potential problems: from mismatching metadata to mutually contradicting prerequisite-outcome structures of underlying resources, from differences in granularity and coverage to ontological conflicts. In this paper, we make an attempt to categorize these problems and give examples from our recent experiment on automated assignment of smart interactive learning content to the chapters of an intelligent textbook in a programming domain.

Keywords: Intelligent textbook · Smart content · Matching conflicts.

1 Introduction

One of the popular directions of augmenting electronic textbooks with value-adding functionality is extending textbooks with “smart content” - interactive examples, simulations, and problems [4]. This direction is very important for the advancement of intelligent textbooks as learners' work with such smart content produces a much more reliable flow of information about their knowledge and skills acquisition enabling better learning modeling approaches and better personalization.

However, the current platforms for development and delivery of interactive textbooks share the same problem: these textbooks are developed “as a whole” with text and interactive problems created together as a part of the authoring process. This approach allows developing excellent examples of interactive textbooks, but does not support scaling up this process.

We advocate a more scalable approach for developing interactive textbooks, such that can make any electronic textbook interactive by augmenting it with smart learning content from existing repositories. An essential problem of this approach is matching smart content items to most appropriate structural units of a textbook. While originally this process has been performed manually, the ability to extract concept knowledge and other metadata from both textbooks and smart content items offers an opportunity to automate this process using AI techniques. In this paper, we review existing approaches for augmenting textbooks with reusable learning content from content repositories and present a novel approach based on smart content annotation with domain concepts automatically extracted from a textbook. In the following sections, we explain our current approach, present expert-based evaluation of the produced results, and discuss problems that have been revealed during this evaluation. We believe that an analysis of these problems will help in constructing more efficient content matching approaches for future interactive textbooks.

2 Related Work

2.1 Smart Content for Computer Science Textbooks

One of the first domains to embrace textbooks augmented with smart content was computer science education (CSE) where development of interactive learning activities from algorithm animations to automatically-assessed programming exercises was a popular research direction [4]. The need to integrate interactive learning activities with online textbooks has been extensively discussed by computer science education community for many years [15] and some of the best examples of interactive textbooks were produced for computer science subjects. Existing interactive textbooks for CSE explored a range of smart content types to extend the core textbook. For example, ELM-ART [6] adaptive textbook for learning LISP included code examples that can be executed online and programming problems that were automatically evaluated by an intelligent program analysis component. OpenDSA [10] textbook for Data Structures and Algorithms included interactive algorithm animations and problems. RuneStone Python textbook [9] included interactive code examples, Parson’s problems, and code construction problems.

At the moment, several CSE research teams develop collections of smart learning content that could be reusable across multiple courses and textbooks. Most of these collections use LTI communication standard that enables smooth connection of smart content items to all kinds of host systems from LMS to LTI-compatible textbook platforms like OpenDSA [10]. Recently, the first catalog of LTI-compatible smart learning content for CSE has been published [11].

This development opens the way to practical application of intelligent content matching technologies discussed in this paper.

2.2 External Content Allocation Approaches

The problem of allocating learning content from content repositories has been explored long before smart interactive content became popular. This direction of research has its roots in similar problems of early learning management systems. While these systems provided space to be filled with all kinds of learning content and facilitated its inclusion, it become evident that a single instructor is not able to create the expected amounts of quality content. To answer the needs of the instructors, various repositories of learning content (also known as learning object repositories) were created. Good examples of these repositories are Ariadne [20] and Merlot [8], which were the focus of many projects exploring the development and use of content repositories. The original model of work supported by these repositories was to help users in finding relevant learning content for specific parts of their courses by offering flexible search tools. Here the needs were expressed by the user through queries, and the search tools helped to find content that matches these needs.

The increased popularity of recommender systems encouraged many researchers to explore the use of recommender technologies to support instructors looking for relevant content [13]. In a typical scenario, by observing user queries and selected content, a recommender system could learn about user needs and intention and recommend matching content that the user might not be able to find by herself [14, 16, 18]. Similarly, the increased popularity of exploratory search systems such as faceted browsing tools, encouraged an alternative approach to help users in finding relevant learning content. Instead of investing in artificial intelligence-based recommendation, these systems seek to augment instructors own intelligence by providing visualization-based tools that helped them understand which concepts are covered by each candidate item [7] and how this item fits into the target place in a course or a textbook [1].

The problem of the current generation of content allocation tools is the amount of human labor they require. The process assumes engagement of domain experts who should analyze each target context where new content should be added, formulate a proper query and examine each candidate item. While recommender systems and content visualization tools help in this process, the whole procedure is still slow and expensive.

In response to this problem, a new generation of content matching tools attempted to further automate the process by building some form of a knowledge model for each target context, building comparable knowledge models for each candidate item, and then engage IR and AI approaches for automated matching. While a human instructor or textbook author might still be required to examine and approve matching results, the speed and the cost of the matching process is decreased considerably making it more scalable. Some early examples of this approach could be found in [19, **?**, **?**]. In this paper, we present and evaluate a new approach for automated matching of smart content to textbook sections. A unique feature of this approach is the ability to reconcile differences between concepts used to index book sections and concepts used to annotate smart content by creating a “bridge” between these concept spaces.

3 Method

3.1 The Textbook

For our experiment on automatic matching of smart content to textbook sections we have used textbook *Python for Everybody - Exploring Data Using Python 3* [17] (PYTHON). We applied our workflow for the automatic extraction of knowledge models from textbooks [2] to the PYTHON textbook. We identified the individual index terms from the Index section of the textbook using the extracted model of the textbook and ensured that these terms represent real concepts within the domain of Pythin programming [3]. Additionally, we collected the set of associated page references for each index term using the model of the textbook. We refer to the index terms as *BookConcepts* in the rest of the paper. In this way, it was possible to link *BookConcepts* to the sections of the textbooks. As a result of this process, each book section get connected to a set of concepts presented in it. We should underline, that these connections are derived from manually constructed textbooks index, hence they represent not just occurrences of terms within textbook pages, but places where corresponding concepts are introduced, explained or elaborated. The overall *BookConcepts* set contained 852 concepts identified in the PYTHON textbook.

3.2 The Smart Content

In this work, we use four smart learning content types from several providers which cover both Python program understanding and construction skills: Animated Examples (52 items in total), Examples-Challenges (42 items in total), Tracing Problems (51 items in total) and Parsons Problems (34 items in total). Each of these items can be individually allocated to a proper place in the course. *Animated Examples* show the step-by-step execution of Python code snippets while making explicit the state of the variables within memory. *Examples-Challenges* are a set of activities that allow students to examine an example which explains how to solve a problem, and then gives them the option of solving a similar problem after where they have to drag-and-drop some lines of code to complete the right solution. *Tracing Problems* are parameterized problems that ask students to predict the output or the final value of a variable after executing a short code snippet. Finally, *Parsons Problems* are puzzle-like problems where the lines of code to solve a problem are presented in an unsorted way so students need to work on putting the lines of code in the right order. More details about the system with these four type of smart content can be found in [5]. All these smart learning activities were automatically annotated with the concepts of a Python ontology by a parser application that extracted concepts from the code of the examples and problems.

From here on, we will refer to Tracing Problems (QuizPET) and Parson Problems as *Exercises*; to Animated Examples and Example-Challenges (Program Construction Examples) as *Examples*; and to the set of concepts from the Python ontology used for annotating the *Exercises* and *Examples* as *SmartConcepts.* In total, the *SmartConcepts* set contained 48 concepts extracted from smart content items (i.e., *Exercises* and *Example*) used in this work.

3.3 The Bridge between the Two Concept Spaces

Given that all textbook sections are annotated with *BookConcepts* and all smart content items are annotated with *SmartConcepts*, it is not possible to match smart content items to book sections directly; first, some connections should be made between these two concept spaces. To create this bridge, all *Exercises* have been manually annotated by the course instructor with corresponding *BookConcepts*: for each *Exercise*, the instructor indicated which *BookConcepts* should be considered as the expected learning outcomes of these problems (i.e., mastery of which *BookConcepts* could be demonstrated by solving a specific exercise). Unlike the textbook, which provides a very broad account of Python programming, the collection of the used coding *Exercises* was much more specific. Hence, the final subset of *BookConcepts* used for annotation included only 47 out of available 852 concepts. Essentially these were the concepts that the learner can master by practicing with the *Exercises.*

3.4 Automatic Content Allocation Procedure

The complete allocation procedure included the following steps.

Assigning book sections to lectures Since we planned to evaluate the approach in a lecture-based class, content allocation was performed lecture by lecture. The first step of the process was assigning a set of book sections as readings for each lecture. As it is usually done in college classes, this step was performed by the course instructor. By assigning readings to the lectures the instructor implicitly specified the *BookConcepts* goal for each lecture, as explained in the next step.

Creating a *BookConcepts* Profile of Each Lecture The goal of this step was creating a formal *BookConcepts* profile of each lecture as a set of *BookConcepts* that each lecture intends to teach. To achieve this goal we first created a full concept profile of each lecture by creating a union of *BookConcepts* from all textbook sections assigned from this lecture and then performed prerequisite-outcome separation process originally suggested in [7]. This process examines each lecture in sequence starting with the first lecture and separates all concepts from the full concept profile of a lecture into *outcomes*, concepts that the learning targets of the lecture and *prerequisites* - concepts that are used in this lecture, but were learning targets of previous lectures. For the first lecture, all of its full profile concepts are considered as outcomes, for the second only new concepts are considered as outcomes while all concepts already appearing the the earlier lectures (even if they are not explicitly mentioned in the lecture) become prerequisites, an so on.

Assigning Exercises to Each Lecture Considering the *BookConcepts* profile of the lecture and the *BookConcepts* annotation of each *Exercise* we assign *Exercises* to the lecture with the highest number for which the following two rules are observed: (1) the *Exercise* should not run ahead of the lecture: all *BookConcepts* of an *Exercise* should be either prerequisites or outcomes of the lecture; (2) the *Exercise* should contribute to practicing the lecture goals: at least one *BookConcept* annotating the *Exercise* should be among the lecture outcomes.

After the first round of automatic exercise assignment, we assessed the results as explained in Section 4.2. The team examined mismatches, determined the sources of problems, resolved problems and repeated the allocation step to reach the 100% correct assignment.

Creating a *SmartConcepts* Profile for Each Lecture A *BookConcepts* profile of each lecture enabled assignment of *Exercises* to lectures since all *Exercises* were manually annotated by *BookConcepts*. It was not sufficient for direct assignment of *Examples* though, as they were only annotated by *SmartConcepts*. The solution comes from the fact that *Exercises* were annotated by both *BookConcepts* and *SmartConcepts*, which created a bridge between the two distinct concept spaces and enabled us to create a *SmartConcepts* profile of each lecture. The process was similar to creating the *BookConcepts* profile explained above – we extracted SmartConcepts from all *Exercises* assigned to each lecture and performed the prerequisite-outcome separation process explained above. The result of this process was a list of prerequisite and outcome *SmartConcepts* for each lecture (in addition to already obtained list of prerequisite and outcome *BookConcepts*).

Assigning Examples to Each Lecture Since every lecture has been now described as a set of *BookConcepts* and a set of *SmartConcepts*, we can run an *Example* allocation process for each lecture by matching *SmartConcepts* from lecture profiles and *SmartConcepts* from *Example* annotations. This process was performed in the same way as *Exercise* assignment explained before, with the difference that *Example* assignment used *SmartConcepts* instead of *BookConcepts*.

After completing *Example* assignment, we performed the second round of evaluation explained in Section 4.3. We discovered and classified additional problems. Following this analysis, all problems were fixed. At the end of this process all *Examples* were assigned to their correct places in the course structure.

4 The Evaluation and Problem Analysis

This section provides the reader with the necessary information regarding the evaluation procedure (in Sect. 4.1) and problem analysis (in Sect. 4.2 and 4.3).

4.1 The Evaluation Procedure

As explained in Section 3.4, we perform expert evaluation of the automatic content assignment procedure twice. First round of evaluation was performed to assess automatic *Exercise* assignment and the second round to assess *Example* assignment. The evaluation was performed from a perspective of a course instructor examining appropriateness of smart learning content for each of the course lectures. The goal of evaluation was to detect misplaced content items and detect potential flaws of the process that led to those misplacements. Every discovered case of a misplacement was recorded and discussed by the team. Through these discussions, we have connected each case to a specific problem which are reviewed below in details since understanding of these problems is critical to improve this and future automatic allocation approaches. It is important to stress that after achieving this evaluation goal in each round, we fixed all discovered problems to ensure that the next round starts with in the correct state. The problems resulting from manual errors were fixed by re-running the allocation procedure. The problems related to conceptual issues of the process were fixed manually by allocating each content item to its agreed proper place.

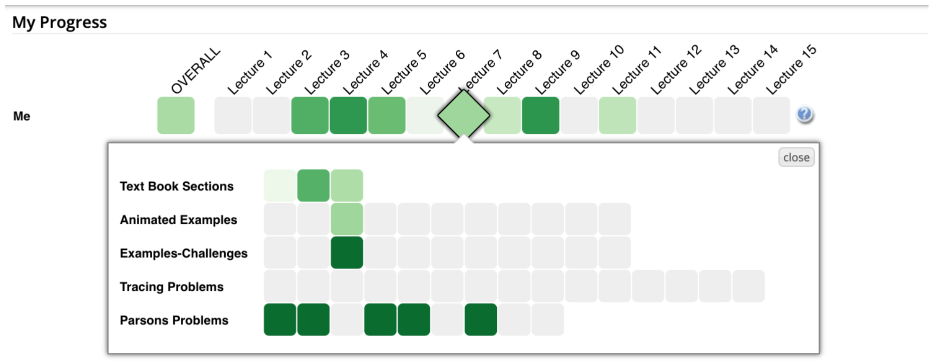


Fig. 1. The MasteryGrids interface with list of learning content allocated for each lecture

To facilitate the evaluation process, we placed all allocated content items into the MasteryGrids interface to experience the content in exactly the same way as an instructor or a student would see it in a course. Figure 1 presents the

MasteryGrids interface. The course is shown as a sequence of lectures. Clicking on each lecture brings up a panel that shows all lecture-related content including book sections, *Examples*, and *Exercises*. Note that green colors that display individual student knowledge and progress were not used in the examination process. From this interface, clicking on a specific content item, provides access to the selected smart content item - see Figure 2 showing an opened example-challenge item. Using this interface, the experts analyzed each automatically-allocated content item assessing its relevance to the assigned lecture.

4.2 Evaluating Exercise Allocation

The key sources of exercise misallocation were manual annotation "glitches". Since manual annotation was done by the single course instructor and without clearly specified rules, the annotation was in several cases inconsistent or incomplete. Most interesting among the observed manual annotation problem was the generality problem. The *BookConcepts* in the textbook form a taxonomy where a number of specific concepts are covered by a more general concept. For example, "for loop" and "while loop" are specific concepts, but both of them are covered by a more general concept "iteration (loop)". Similarly, Python prescribes several specific cases of indentation in loops, functions, conditional statements, etc, but all of these specific cases are covered by a more general concept of "indentation".

It is natural that most textbooks introduce general concepts when two or more specific cases were presented. I.e., in the PYTHON book, the first code examples with indentations were introduced in Chapter 3, but it explicitly appears as a concept and becomes a part of the *BookConcepts* profile of a section only in Chapter 4, by which time several indentation cases are presented and the introduction of this general concept becomes meaningful. Due to this role of more general concepts, many cases where the instructor used a general *BookConcept* (like "iteration (loop)" or "indentation") lead to exercise misplacement. I.e., if an exercise that really belongs to Chapter 3 was indexed with "indentation" (because, indentation was featured in the exercise code) it will be allocated to Chapter 4 since this is the first place where this *BookConcept* appears.

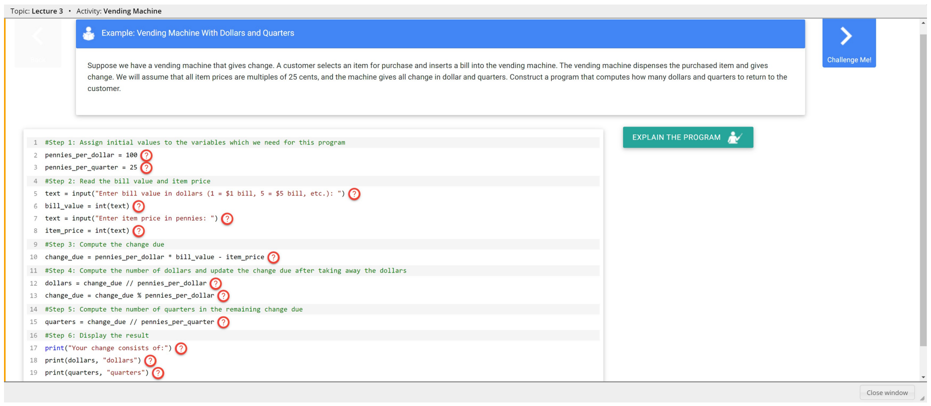
We concluded that all observed manual annotation issues could be resolved by creating more formal rules of annotation assembled in a "codebook", for example, as suggested in [21]. One of these rules should be exclusion of overly general concepts like loop, indentation, statement, etc. from content annotation. To fix these problems, the instructor reviewed annotations of *Exercises* making them more consistent, removing more general concepts and only keeping the specific ones. For example, "iteration" as an initial concept was replaced by "for loop" and "while loop". After that, automatic exercise allocation process was repeated, which fixed all the observed errors.

4.3 Evaluating Example Allocation

In total, our automatic content allocation procedure assigned 94 *Examples* to the lectures. Among them, 80 *Examples* were allocated correctly and 14 had to be manually reallocated. In other words, the automatic content allocation was successful more than 85% of the time. The cases of wrong example allocations were distilled to two main groups of issues, namely *coverage-related* and *parser-related* (imperfect matching) issues which are explained below.

Coverage-related issues Coverage-related issues have their roots in clusters of similar concepts in programming languages, such as a set of *arithmetic operation* concepts, that are usually learned together in the same lecture. Due to their similarity, instructors rarely pay attention whether or not all of these concepts are covered by lecture *Examples* or practice problems. This is what happened more than once in our case. Despite several *Exercises* specifically targeting simple arithmetic operations, all correctly allocated to Lecture 3, none of them included "floor division" operation. As a result, "floor division" concept has not been added to the *SmartConcepts* profile of Lecture 3. At the same time, "floor division" appeared as a part of code in one of Lecture 5 problems. While it was a side concept there, it was the first lecture where "floor division" appeared and it was added as one of the outcomes to the Lecture 5 *SmartConcepts* profile.

However, some of the *Examples* focusing on practicing arithmetic operations did include "integer division" in their code. (see Figure 2). The parser successfully identified "floor division" concept in this *Example*'s code (see Lines 12 and 15) and included it in its annotation. As a result, this *Example* was allocated to Lecture 5 instead of its correct placement in Lecture 3.


Topic: Lecture 3 • Activity: Vending Machine
Example: Vending Machine With Dollars and Quarters
Challenge Me!
EXPLAIN THE PROGRAM
Close window

Suppose we have a vending machine that gives change. A customer selects an item for purchase and inserts a bill into the vending machine. The vending machine dispenses the purchased item and gives change. We will assume that all item prices are multiples of 25 cents, and the machine gives all change in dollar and quarters. Construct a program that computes how many dollars and quarters to return to the customer.

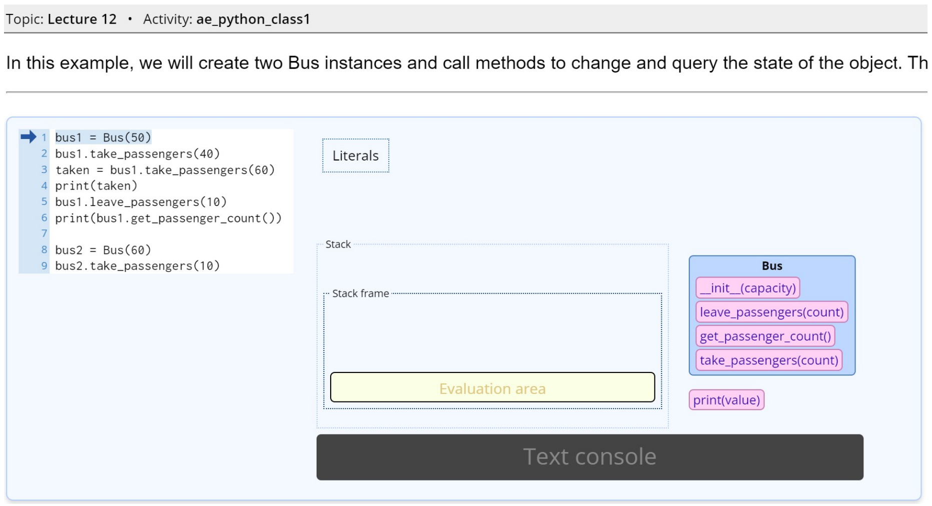
```
1  #Step 1: Assign initial values to the variables which we need for this program
2  pennies_per_dollar = 100
3  pennies_per_quarter = 25
4  #Step 2: Read the bill value and item price
5  text = input("Enter bill value in dollars (1 = $1 bill, 5 = $5 bill, etc.): ")
6  bill_value = int(text)
7  text = input("Enter item price in pennies: ")
8  item_price = int(text)
9  #Step 3: Compute the change due
10 change_due = pennies_per_dollar * bill_value - item_price
11 #Step 4: Compute the number of dollars and update the change due after taking away the dollars
12 dollars = change_due // pennies_per_dollar
13 change_due = change_due % pennies_per_dollar
14 #Step 5: Compute the number of quarters in the remaining change due
15 quarters = change_due // pennies_per_quarter
16 #Step 6: Display the result
17 print("Your change consists of:")
18 print(dollars, "dollars")
19 print(quarters, "quarters")
```

Fig. 2. Presentation of an Example-Challenge in MasteryGrids. The shown example demonstrates a coverage-related issue (missing "division" arithmetic operation in Lines 12 and 15).

In our evaluation study, we observed 4 coverage-related issues which had to be reallocated manually. This reallocation comprised 4.2% of all cases. A possible long-term solution for this category of problems would be using concept grouping techniques: a set of concepts (such as “arithmetic operations” that are usually introduced and practiced together should be combined into an “unbreakable group”. Whenever one of the concepts in such a group is added to a set of concept outcome of a specific lecture, the rest of them should be added too.

Parser-related issues (imperfect annotation) Several misallocation cases were traced to the insufficient sensitivity of the parser used to extract *SmartConcepts* from the code of smart content items. Most of these errors were related to the minimalistic approach to syntax in Python where the same syntactic form is used to express concepts that are semantically or pedagogically different. For example, the parser was not able to recognize important file operations `open(file)` and `file.close()`, since from syntactic prospect, these cases are not different from any other functions or methods. As a result, instead of being assigned to a lecture covering work with files, these *Examples* were misallocated to a lecture on functions and methods. We had to reallocate three examples of this kind, which comprised 3.2% of *Examples*.

Similarly, the parser was not able to identify the use of a “class constructor” as a special case since it was also looking just like any other function call (see Figure 3). It resulted in misallocation of two examples which were not placed into a lecture on object-oriented programming where they belong. We had to manually reallocate two *Examples* of this kind, which comprises 2.1% of all *Examples*.


Topic: Lecture 12 • Activity: ae_python_class1

In this example, we will create two Bus instances and call methods to change and query the state of the object. Th

```
bus1 = Bus(50)
bus1.take_passengers(40)
taken = bus1.take_passengers(60)
print(taken)
bus1.leave_passengers(10)
print(bus1.get_passenger_count())

bus2 = Bus(60)
bus2.take_passengers(10)
```

Fig. 3. Presentation of an Animated Example in MasteryGrids. This example demonstrates a parser-related issue (inability of detecting creating object from a Class).

Yet another example, is a parser's failure to recognize a special case of `.format()` expression. The corresponding *Examples* should have been allocated to the "string methods and regular expression" lecture, but for our parser it was looking just like any other attribute causing these *Examples* to be misallocated. To fix this issue, we had to reallocate five *Examples* from the prior lecture to the corresponding lecture (5.3% of the *Examples* set).

All of these cases point to the weakness of the current parser version. A long-term solution to the observed problem is to refine the parser so that concepts that are similar syntactically but different pedagogically are recognized as different concepts. When developing a concept parser for Java [12] we achieved this goal by creating a syntax-independent Java ontology and creating rules to match leaves of Abstract Syntax Tree to ontology concepts. For Python, however, we used a simplified version of the parser.

5 Conclusion and Future Work

In this paper, we presented the first evaluation of our automatic smart content allocation procedure based on automatic annotation of a textbook and a collection of smart content for programming. We focused the paper on examining cases of misallocation detected during expert evaluation process. We believe, this analysis is important for the progress of research on automated content allocation and enrichment of textbooks with interactivity. We are currently running a classroom study to explore to what extent the results of our automated allocation were acceptable to students. In our future work, we will focus on resolving the problems discovered in this study through developing a content allocation "codebook" for instructors and a better version of the smart content parser.

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