The Y-Model - Formalization of Computer Science Tasks in the Context of Adaptive Learning Systems

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***Abstract*—Tasks, understood as educational instructions to transform an initial state to a targeted state in the learner model, are central elements in (computer science) education, irrespective of the mode of delivery – online or classic face-to-face teaching. They appear in different roles; as learning objects that help acquire competencies, as assessment instruments for measuring learning success, or for practicing specific skills. However, as with any educational technology, proper handling and well-planned selection are crucial for successful teaching. Correspondingly, the requirements that tasks have to fulfill are wide-ranging: they should promote specific learning outcomes, be appropriate to address desired cognitive dimensions, and be tailored to the student to keep motivation and learning success high. To enable an on-demand, outcome-oriented, and individualized selection of tasks in adaptive learning systems, we need to formalize tasks in all dimensions. A detailed review of different models for cognitive processes, knowledge dimensions in education, tasks, and errors leads to the *Y-Model*, a model for formalizing tasks (in computer science). It forms the basis for an individual, competence-oriented integration of tasks in educational systems. Finally, we present the first implementation of the model.**

This paper uses LaTeX3. The semantically annotated XHTML version of this paper is available at https://url.mathhub.info/23GeCon. This also incorporates (some of) the features discussed in Section III.

I. Introduction

The number of students in STEM subjects and the industry's need for well-educated computer scientists is increasing. However, not only do many learners challenge teachers, but also the rise of heterogeneity in terms of prior knowledge, social background, and learning performance[1]. Combined with fundamentally scarce resources, this creates a strong demand for systems that (partially) automate grading and feedback [1, 2], as well as systems that support handling heterogeneity [3].

While modern learning environments, such as adaptive learning systems (ALSs), aim to address this heterogeneity by customizing learning content and providing timely tasks and feedback [4], the majority of ALSs currently available only provide a predetermined and unchanging sequence of learning tasks with simple feedback [5, 6]. A predefined task sequence is not equally suitable for individual learners who can differ in many facets, such as prior knowledge, personality, and learning speed [7].

The provision of tasks can have different reasons. They can be used to check learning success, teach new content and concepts, or practice them. They are very complex entities and therefore the subject of research in computer science education [8].

Here, we address how tasks can be *formalized* to enable processing by an adaptive system during a selection process. Specifically, we investigate the application of the *Y-Model* for annotating tasks with desired preconditions and learning objectives, which facilitates the selection of tasks tailored to a learner's needs. Our research aims to provide insights into how the formalization of tasks can enhance the capabilities of adaptive learning systems and how such systems can be optimized to better serve the learning objectives of individual students. Through our investigation of the Y-Model, we aim to identify best practices for task formalization that can improve the effectiveness of adaptive learning systems and, ultimately, contribute to advancing computer science education.

II. Representing Tasks with the Y-Model

The model subsumes all elements involved in the representation of tasks, namely, cognitive processes, knowledge elements, task descriptions, and answers (see Figure 1). The components of the Y-Model are explained accompanied by a running example task (see Figure 2).

A. Task

In terms of competency-based teaching, tasks are a vital part of a teacher's pedagogical knowledge [9] to develop and/or select tasks on which learners can acquire and enhance the targeted competencies [10, 11, 12, 13]. Tasks have various purposes: they are suitable for imparting knowledge, can be useful to practice what has already been taught, and are essential for checking a learner's success.

In the context of teaching, most definitions of "task" emphasize a prompt and its processing by the student [14]:

Ruf et al. [8] define a task as an instruction (*to do*) to transform a given state (*given problem*) into a desired final state (*expected solution*). Between the initial and final states, knowledge is transformed using a cognitive process. For instance, the (programming) task in Figure 2 has the **given**

[1] https://www.bcs.org/articles-opinion-and-research/record-numbers-of-students-choose-computer-science-a-level-in-2022/

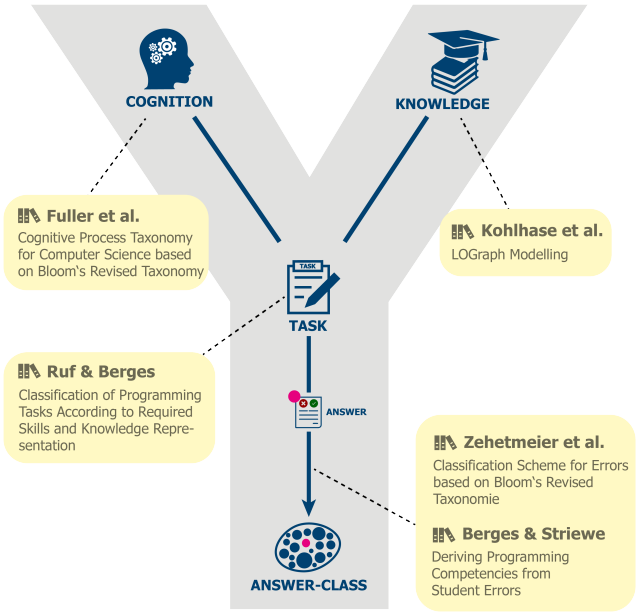

Fig. 1: The Y-Model.

Task

Given the following empty class body `Homework3` in Java:

```
1  public class Homework3 {
2      // Code here
3  }
```

Implement a method `minSearch` which receives an array of integers as input and returns the minimum of those numbers.

Fig. 2: Running Example.

state "empty class body `Homework3`", and the **desired state** "class `Homework3` with a method `minSearch` that returns the minimum value of a given array of integers".

B. Knowledge Element

There is no universal definition of the term *knowledge* across domains. For example, philosophical-epistemological treatments of knowledge usually require known propositions to be *true*. In education, there is a substantial distinction between competencies and knowledge. While the former focuses on the observable outcome and often refers to the definition of Weinert [15], the latter is described as the representation of information in memory [16].

In contrast, for our purposes *knowledge* is anything amenable to techniques developed in the field of *knowledge representation*. Knowledge, in this sense, neither needs to be correct, believed, or even propositional, nor does it need to be associated with any cognitive abilities.

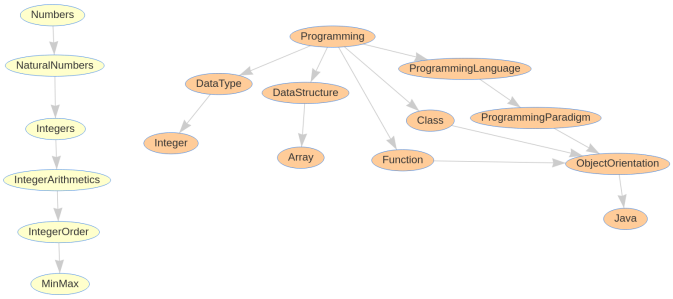

Fig. 3: Theory Graph of Concepts from the Running Example.

In other words, in the context of the Y-Model, *knowledge* is understood pragmatically as any information contained in some course materials. Additionally, this includes tasks that have to be represented in a form actionable by a machine that can provide added-value services, including curating and selecting tasks and providing feedback on students' answers to a given problem.

Thus, an essential aspect of the knowledge component of the Y-Model is *structural*: how does a piece of information relate to the broader body of knowledge? What must a learner already know to understand it or to complete an associated task? Which knowledge elements does a given problem *evaluate*?

In the domain of knowledge representation, knowledge elements are often represented in *knowledge graphs*. Knowledge graphs provide a structured representation of a given body of knowledge with nodes representing fundamental knowledge elements and edges relations *between* knowledge elements. The exact nature of knowledge elements and relations can vary widely (for a recent overview, see [17]).

C. Cognitive Process

To solve a task, the existence of pure knowledge is not sufficient. Specific cognitive processes are required to retrieve the knowledge or to apply it to a problem. However, the concrete cognitive processes involved in solving a task remain a black box for the teacher, but they are crucial for observable objectives in the sense of competencies.

A variety of taxonomies already exist to describe and classify cognitive performance. In higher education, Bloom's taxonomy [18], or its revised version by Anderson & Krathwohl [19] (AKT) are often used.

Anderson & Krathwohl rearranged Bloom's cognitive process dimensions to 1) `remember`, 2) `understand`, 3) `apply`, 4) `analyze`, 5) `evaluate`, and 6) `create`. Based on AKT, Fuller et al., [20] developed a taxonomy explicitly applied to the computer science context, which we use in the Y-Model for modeling the cognitive dimension. Nevertheless, our current implementation only uses AKT due to the smaller number of cognitive dimensions.

Johnson and Fuller confirm that even experts often disagree on which cognitive category to place a task in [21]. The Y-Model only annotates which cognitive dimensions is intended

in connection with a knowledge element when processing a task. It does not generally determine which task requires which cognitive processes to solve it successfully. The latter would only be possible by modeling the user and is the goal of future work.

D. Answer Classes

A given answer to a task provides a valuable source of information in the context of teaching. In a sense, answers result from applying cognitive processes to the learning content addressed in the task. Thus, an answer provides evidence for the teacher about the student's performance. The selection of the subsequent tasks in the learning process and individual feedback also heavily depends on the learner's answer to a task.

In the Y-Model, given answers are grouped into *answer classes (ACs)*, which can be represented in set-theoretic propositional form. Let R be a possible response to a task and B be an observable description of the state of this task. We say that R is an element of the answer class AC_x, if R meets all the requirements of description B. Formal:

$$AC_x = \{R \,|\, R \text{ meets all the requirements of description } B\}$$

We always understand requirements that determine an *AC* to be observable (e.g., cognitive processes are not considered).

Table I shows some examples of *AC*s for the task *minSearch* (see Figure 2):

ID	answer class
AC_1	$\{R \,\|\, R$ compiles with Java-Compiler Version X$\}$
AC_2	$\{R \,\|\, R$ includes a syntax error$\}$
AC_3	$\{R \,\|\, R$ outputs the minimum of an array correctly$\}$
AC_4	$\{R \,\|\, R$ includes a while- or for-loop$\}$
AC_5	$\{R \,\|\,$ use of `System.out.println` instead of `return`$\}$
AC_6	$\{R \,\|\,$ use of Java API$\}$
AC_7	$\{R \,\|\,$ edge case for empty array is missing$\}$

TABLE I: Possible answer classes for the running example.

Since the task description does not contain any further restrictions, various approaches provide an accepted solution:

For instance, the minimum value of the passed array could be returned using the Java API, e.g. first sorting in ascending order and returning the first element or using the min-function ($R \in AC_1 \cap AC_3 \cap AC_6$). On the other hand, the task can be successfully solved without an API call using a for-loop to iterate through the array and use a variable `min` to locate and output the minimum value. ($R \in AC_1 \cap AC_3 \cap AC_4$).

A significant advantage of grouping answers into *AC*s is the opportunity to provide feedback more efficiently. If the answer classes are developed wisely, it is sufficient to provide feedback for them, rather than for each individual answer. However, the challenge remains in a diagnosis to map answers to the appropriate *AC*s. In the context of programming tasks, this can be done by static and dynamic code analysis, or just manually by a teaching assistant (see for instance [22, 23]).

III. Y-Model in action

We will now evaluate the Y-Model – derived from theoretical requirements – via concrete applications in the ALEA system (Adaptive Learning Assistant) [24], which is developed within the VoLL-KI project (see https://voll-ki.de).

We use the sTEX system [25, 26], a LaTeX package and associated software ecosystem for augmenting document fragments with semantic annotations. Besides being standard LaTeX, which is familiar to many teachers in STEM fields, sTEX documents can be converted to HTML and imported and processed by MMT [27], an API for generic knowledge management services.

Both MMT and sTEX organize individual knowledge elements in *modules*, which may import and extend other modules analogously to object-oriented programming. This allows for representing knowledge as an interconnected *theory graph* of modules (see Figure 3). In particular, sTEX has previously been used to semantically annotate thousands of pages of university course materials using reusable libraries with > 2250 concepts.

A. Task annotation

Once authors have chosen a proper context, they can semantically annotate their task by following the Y-Model.

sTEX provides a custom environment for *problems*/exercises (see Line 1 in Figure 5). Our particular example task depends on the modules for the programming language Java, integer and array datatypes, and the minimum function on sequences of integers (Lines 2–5). The modules imported from the theory graph represent the task's *learning context* from Figure 3. The declarations in these modules can subsequently be used to annotate their occurrences in the text (Lines 9–19), referenced via `\sn`.

However, we cannot infer from the mere task description what the educational goals of the task are, which requires additional, context-dependent annotations:

Setting the *objective* is a modeling decision that specifies which competencies a user is believed to acquire or demonstrate when working on the assignment. In our running example, the objective is the pair $\langle \texttt{apply}, \texttt{array} \rangle$ (see Line 7). This competency might be cross-validated by further tasks (for example, to rule out that the user just memorized the solution without any deeper understanding).

Tasks not only carry information about their *main* objectives, but also about (implicit) *preconditions*. Like objectives, these are modeled as pairs of cognitive dimensions and knowledge elements (see the upper part of Y-Model in Figure 1). sTEX `\sn` annotations already give us many such preconditions: all concepts (referenced via `\sn`) in the task (recursively) entail preconditions with the cognitive dimension `remember`. Additional preconditions can be annotated with the `\precondition` macro: the running example presupposes a basic understanding of a "minimum" – not just `remember` (line 6).

To assign given answers to their respective answer class, they have to be annotated as well – either by human correctors or (in future work) by automated clustering algorithms. Line

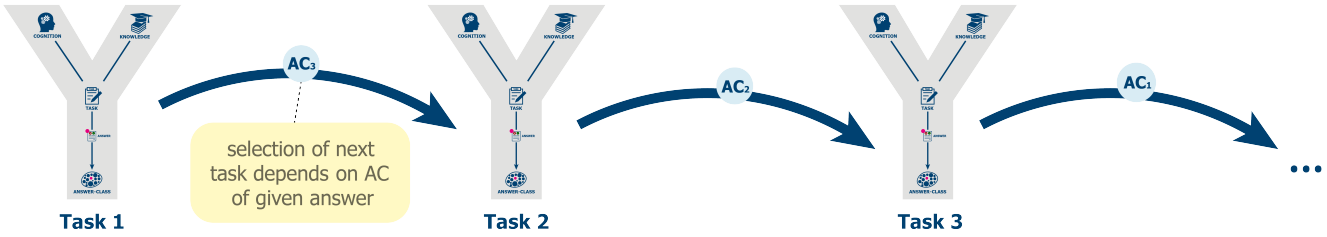

Fig. 4: Selection of tasks based on *AC*s (and optional learner model).

```
\begin{sproblem}
  \import{Java}
  \import{datatypes?Integer}
  \import{Array}
  \import{MinMax}
  \precondition{understand}{MinMax?minimum}
  \objective{apply}{array}

  Given the following empty \sn{class-body} \texttt{Homework3}:
  \begin{listing}[language = Java]
      public class Homework3 {
          // Code here
      }
  \end{listing}

  Implement a \sn{method} \texttt{minSearch} which receives an
  \sn{array} of \sn[integer]{integers} as \sn{Function?input}
  and returns the \sn{MinMax?minimum}
  of those \sn[number]{numbers}.

  \answerclass{AC7}{..\aclasses\ac7.tex}
\end{sproblem}
```

Fig. 5: The Running Example in LaTeX, Semantically Annotated (STEX syntax slightly simplified for clarity.)

21 provides one possibility for such an annotation as a pair of a unique identifier and a file containing information about the answer class, e.g. metadata for feedback generation.

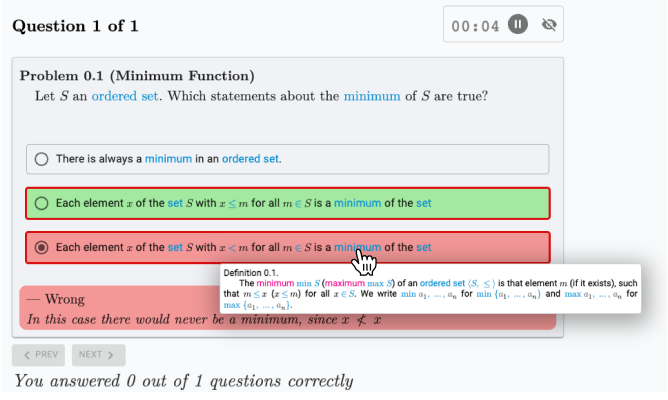

Fig. 6: Follow-Up Task with Hovering Event in the ALeA System.

B. Task selection

Educators can use the Y-Model annotations to tailor tasks to specific concepts via their preconditions and learning objectives – not only for task selection, but also for *sequencing*: the automatic selection of follow-up tasks based on user-provided answers. Consider a scenario where a learner is presented with the running example as part of an introductory programming course in the ALeA system, but struggles with the preconditions and requests assistance. Subsequent tasks that contain these as learning objectives can then be automatically selected. In our case, a learning object aimed at improving the understanding of a minimum could be chosen, e.g. an explanatory text, a definition (with instructions to read it), or a multiple-choice test. Figure 6 shows a task in the ALeA system that could be displayed to the learner in this scenario.[2] Based on the learner's answer, further tasks can be subsequently selected (see Figure 4).

As for all ALeA materials, learners can see definitions by hovering over annotated references to concepts. We leverage this concept to offer *guided tours* – on-demand sequences of learning objects tailored to acquire competencies for specific knowledge elements in particular cognitive dimensions (i.e., specific learning objectives). Presently, these guided tours comprise only definitions that arise from the dependencies.

Furthermore, *flashcards* can be generated from the annotated course materials (see Figure 7), without the need for additional authoring. They can serve as self-assessment tools for concepts, currently only for the `remember` and `understand` dimensions.

By incorporating *learner models* that estimate a user's competencies, such services can be further enhanced. In our system, these models are represented as maps from pairs ⟨cognitive dimension, knowledge element⟩ to values in $[0, 1]$, allowing for even more precisely task meeting a learner's needs by factoring in their (estimated) prior knowledge.

Apart from task selection and service provision, Y-Model annotated tasks offer other benefits as well, such as providing information for updating a learner model, with answer classes being particularly significant. For instance, the results of the self-assessment tests in flashcards update the learner model, further improving the efficacy of the ALeA system.

[2] see https://url.mathhub.info/gdpquiz

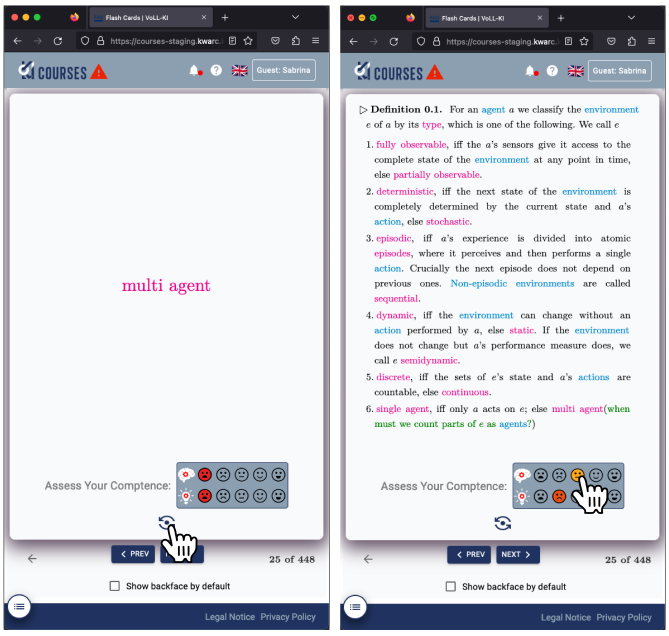

Fig. 7: Flashcards in ALeA System.

IV. Conclusion and Future Work

The knowledge elements and cognitive dimensions of tasks were cast into a model using existing models and current research. In addition, *answer classes* were modeled, significantly expanding the possibilities for individual feedback and task selection processes in adaptive learning systems. The presented technique for semantic annotation of course materials (Section II-B) is currently limited to the use of LaTeX documents, but the theoretical model is not. Experiments for extending office suites and markdown with STeX-like annotations are ongoing so that annotation of common formats will be possible in the future.

Semantic annotation via the Y-Model acts as an interface between the teacher's pedagogical content knowledge and adaptive learning systems. It supports multiple learning support services, such as generating individualized feedback and updating a learner model. Although the current focus is on computer science-related tasks, the Y-Model generalizes well to other areas with minor modifications.

Formalizing tasks alone is insufficient to enable individualized learning in an ALS. The Y-Model focuses mainly on task-specific criteria for task selection. However, it also depends on learner-specific criteria for determining which task is appropriate to achieve a particular learning level and promote selected competencies – each student has an individual educational biography [28]. A learner model is necessary to model individual competencies and integrate them into the decision-making processes of the system. Ongoing research examines how the Y-Model and a learner model can be effectively combined to generate valuable feedback and task selection. Additionally, this research investigates the challenges that arise during the integration process. Materials of six courses have already been semantically annotated according to the Y-Model. At https://courses.voll-ki.fau.de, more than 1000 students already have access to the ALeA system, where guided tours and flashcards can be generated automatically from the annotated course materials.[3] Further learning objects, such as quizzes, annotated with the Y-Model, are under development and will be integrated into the system as a next step.

The presented model is a theoretical underpinning for different applications of integrating tasks in adaptive educational technology like adaptive learning systems. The generation of adaptive feedback and hints is planned as future work. Existing systems mainly generate simple feedback that only focuses on the errors themselves, but do not address the causes of the errors [5], which is considered valuable feedback from a student perspective [29]. Combining the Y-Model with a learner model, we will explore techniques to infer the causes of errors to provide better feedback.

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[3] see https://url.mathhub.info/flashcards

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