Working at your own Pace: Computer-based Learning for CL

Anselm Knebusch and **Ulrike Padó**
Hochschule für Technik Stuttgart
Schellingstr. 24
70176 Stuttgart
firstname.lastname@hft-stuttgart.de

Abstract

Introductory Computational Linguistics (CL) classes are often made up of students from different fields of study, most commonly CL, Linguistics or Computer Science (CS) – all of whom have different expertise and perspectives on the subject. Even among students of a single program, learning speeds and previous experience vary widely.

The teaching method of Computer-based Learning (CBL) was developed specifically to address this type of heterogeneity among students. It aims to combine the advantages of on-line and in-presence teaching: Students do self-paced work on video inputs, feedback tests and practical exercises while the professor is available in the room for questions and discussions. In this way, the method can accommodate different learning speeds as well as different levels of previous knowledge and different study backgrounds.

We demonstrate the method using the CL content of a class on Artificial Intelligence in the CS Bachelor's program at Hochschule für Technik Stuttgart as an example. We outline the CL content and describe one class in detail. Student and teacher feedback from this class and two more classes taught through CBL show the method's strengths and its suitedness to all phases of study, be it in the first semester, the final semesters or mid-program.

1 Introduction

Computational Linguistics (CL) integrates methods and levels of description from two disciplines with very different approaches and cultures. In dedicated CL programs, introductory courses on CL are therefore usually taught to heterogeneous groups made up from students of CL programs as well as students from Computer Science (CS), Linguistics, and Language and Communication programs that take CL as a minor subject. Depending on their original field of study, these students have very different previous knowledge and motivation for taking a CL course. This challenges professors to teach concepts from CS to Linguistics students and concepts from Linguistics to CS students without duplicating material that CL students are learning in other classes in their own programs.

A second source of heterogeneity in the student body is differences in students' educational biographies and work experience. This is especially pronounced at Universities of Applied Sciences (Hochschulen für Angewandte Wissenschaften or Fachhochschulen, collectively called HAW hereafter), which have an applied focus, prepare their students primarily for a career in industry and accept students from a large variety of educational backgrounds. At the same time, there are no CL or Linguistics Bachelor's programs at HAW, according to *Hochschulkompass der Hochschulrektorenkonferenz (HRK)* [1], so CL topics are taught primarily to students from CS, Communications, and related programs and usually in program-specific classes.

Despite these structural differences, both at Universities and HAW, the main challenge to teaching introductory topics in CL is heterogeneity in students' previous knowledge and experience (see, for example, Banscherus, 2013). In this situation, learning paths need to be individualized, offering each student the materials they need in order to make the most of the class. This has to be done, however, with a limited amount of teaching staff - especially at HAW, where teaching is done almost exclusively by professors and very little additional teaching staff is available. To address these challenges, a blended learning setting is arguably the most suitable approach (see, for example, Garrison and Kanuka, 2004).

[1] offered by Deutscher Akademischer Austauschdienst: https://www.daad.de/de/studieren-und-forschen-in-deutschland/studienprogramme-sprachkurse/alle-studiengaenge/

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We present the blended-learning method of Computer-based Learning (CBL, Knebusch et al., 2019) which allows students to choose their focus during self-paced learning with frequent feedback through formative tests and with hands-on exercises, while freeing up professors to answer individual questions, give additional input and discuss advanced topics as needed.

We demonstrate the method using the example of an Artificial Intelligence (AI) class which contains a significant amount of CL content and is taught to students in the third semester of the CS Bachelor's program at Hochschule für Technik (HFT) Stuttgart, a HAW. We motivate the selection of the CL-related topics chosen for this class and describe an example session.

We argue for the appropriateness of the method by analysing structured student feedback on this class. Additionally, we discuss professors' impressions and structured student feedback from two other CBL classes taught to demonstrate the versatility of the method across stages of study.

We begin by characterizing teaching at HAW to give some context to the Hochschule für Technik class before introducing the CBL method and the CL content taught in the example class. We finish by discussing student and teacher feedback.

2 Teaching at Universities of Applied Sciences

At HAW, students are heterogeneous with regard to their educational careers and experience: Some matriculate directly after school, others may have work experience in a related field. In accordance with the practical focus of HAW, students are generally interested in and very good at applied work and enjoy project tasks.

Many HAW students are the first academics in their families. This often means that they have little financial support, which can manifest in long commutes to the university and a need to work in parallel to their studies (Bargel and Bargel, 2010). Therefore, students especially value the ability to work on class content independent of the scheduled time and place.

Teaching programs are highly structured and teaching is done almost exclusively by the professors, with little to no support staff. This means that there are no time ressources for providing feedback through grading weekly exercises or for individualized support through many parallel tutorial groups.

3 Method: Computer-based Learning

The main goal of Computer-based learning (CBL, Knebusch et al., 2019) is addressing heterogeneity and providing an optimal learning experience through a tailored and adaptive learning environment. CBL achives this by incorporating times of self-study into the traditional lecture. This is a contrast to the well-known concept of the Inverted Classroom (IC, also known as "flipped classroom"), where students are provided with video lessons to watch in preparation for an in-presence session (Loviscach, 2011).

IC has been shown to support individual learning speeds and pathways, as well as self-directed learning (Dreer, 2008; Lage et al., 2000). However, as the highly-structured curricula at HAW result in a large number of teaching sessions per day for students, implementing a flipped classroom approach for many classes would likely overwhelm the students in terms of required preparation time. Additionally, especially at the beginning of their studies, students may not have developed the self-directed learning skills necessary for the flipped classroom approach.

Instead, CBL mixes instruction and exercises during the scheduled class hours, leveraging live lectures and digital resources such as instructional videos to solidify understanding and bridge knowledge gaps. Moreover, the in-presence setting provides a supportive framework for new students, allowing them to engage in collaborative work, seek guidance from peers, and benefit from expert assistance from instructors. In this way, CBL allows for a high level of individualization while capitalizing on the advantages of face-to-face teaching. Overall, CBL has been shown to promote active learning, maximize students' time spent on task, and facilitate individualized support, leading to improved learning outcomes for first-semester students. (Knebusch et al., 2019)

CBL is best suited for project- or task-based courses, where tasks can be divided into manageable steps. The students work on "Learning Nuggets," which consist of short traditional lecture input, instructional videos, feedback questions, and exercises and apply their new knowledge incrementally to their tasks or projects, transitioning between passive and active learning phases. This approach not only enhances student engagement but also allows for a seamless transition between individual, partner, or group work.

In CBL, assessment and feedback play crucial roles in guiding students' learning journeys. Regular formative assessments, quizzes, and project evaluations are conducted to measure students' progress and provide timely feedback. This feedback helps students identify areas for improvement and adjust their learning strategies accordingly. Additionally, instructors actively engage with students, providing one-on-one discussions to set goals, monitor progress, and offer personalized feedback, thereby supporting students' self-regulation and growth.

CBL was originally developed at HFT Stuttgart as part of the "Qualitätspakt Lehre II" for basic Mathematics courses in engineering programs. Building upon positive evaluation results in Mathematics, we have recently transferred the concept to the CS program, especially in classes for Machine Learning and AI.

3.1 Adapting Existing Materials

When re-framing a traditional class for CBL, existing lecture inputs are broken into shorter learning nuggets and immediately followed by student activities such as self-tests for feedback or matching exercises. Existing materials such as slides and exercises can often be re-used at this step. It is helpful to give (near-)immediate feedback on exercises to help students check their work incrementally during self-study. Self-tests usually have to be created from scratch and will likely require calibration after the first iteration of the class to ensure that the questions work at the desired difficulty level (easy for a comprehension check after a lecture input, harder for practice and exam preparation).

The initial lecture input can be given as a traditional live lecture, but later inputs need to be recorded to provide the self-study input videos. Existing lecture videos can be reused, provided their quality is appropriate. Unfortunately, this is often not the case for pandemic-era lecture captures in our experience, because these tend to be too verbose or to contain errors, delays and interactions with individual students. Video inputs should be concise and to the point, focusing on one specific sub-topic. Since video inputs are generally short (10-15 minutes), a simple screen capture of lecture slides with a voice-over can be used, even though this type of input can be tiring to work through for longer stretches. In sum, re-framing a traditional lecture-and-tutorial setup requires a substantial investment of time and effort, but is not comparable to designing a class from scratch. Also, it is possible to translate only some classes to CBL at first and space out the adaptation over several semesters in this way.

The question of which portions of a class to reframe (and at what speed) can most easily be answered given the professor's reasons for switching to CBL. These will likely be a desire to increase student activity during the lectures, exposure to practical work and involvement with the class. With these in mind, the professor can determine the extent of re-framing needed and prioritise individual classes as needed.

At the same time, on the level of individual lectures, re-framing for CBL is a good opportunity to evaluate the lecture focus on the different aspects of the content and to check the match between lecture inputs and exercises, as well as identifying opportunities for giving students immediate feedback on their progress through tests.

3.2 Evaluating CBL for Advanced Classes

In the process of adapting CBL to instruction in CS, we surmised that CBL is also well suited for more advanced courses, since in later stages of studying, the students already have good self-directed learning and collaborative skills and often prefer working at their own pace. In the following, we will demonstrate the use of CBL for teaching CL content to CS students and evaluate our assumption by reporting student and professor feedback on the use of CBL in three different stages of studies: In the first semester (Mathematics for Civil Engineers), at the beginning of Hauptstudium (third semester, AI for CS) and in an elective module in the final semester of study (Machine Learning and Data Mining for CS). We find evidence that CBL is indeed well-suited for teaching heterogeneous groups throughout the whole study program, new as well as experienced students.

4 Content: Computational Linguistics Topics

At HFT Stuttgart, one opportunity to teach CL to students in the CS Bachelor's program content is as part of a semester-long AI class in students' third semester of study (after completion of the two initial semesters of Grundstudium).

The class uses Russell and Norvig's structuring of the field of AI (Russell and Norvig, 2016), covering topics in "Problem Solving", "Knowledge, reasoning and planning", "Learning" and "Communicating, perceiving and acting". The CL content is covered mostly under this last heading, although some of it also falls under Learning. In detail, the covered topics are

- Introduction to human and human-machine dialogue (Communicating)
- Introduction to morphology and surface normalization (Communicating)
- Text classification with bag-of-words features (Learning)

The topics are chosen in such a way that the students encounter engaging practical tasks and projects and at the same time gain a background understanding of AI techniques that have become ubiquitous in their daily lives. Given the students' existing background in software development and computing, the input is geared towards providing concepts from Linguistics and is intended to demonstrate the complexity of the tasks and the resulting need for careful treatment and analysis of language data.

One topic cluster addresses dialogue and handling of written text, using a tiny Java chat bot[2] and an open-source personal assistant[3] as motivating examples. The students learn about properties of human-human dialogue and expand the chat bot code accordingly, e.g. to cover greetings and appropriately complete other adjacency pairs. Adding functionality to the chat bot motivates additional input about morphology and surface normalization of text and experimentation with existing tools[4]. The Learning task additionally teaches about Machine Learning methodology and treatment of text as training data, both through CBL-based classes and a practical project in which students train a text classifier on a small data set[5].

[2]adapted from https://www.python-lernen.de/chatbot-programmieren.htm

[3]Mycroft, https://mycroft.ai/get-started/

[4]Students explore GermanNet Rover, https://weblicht.sfs.uni-tuebingen.de/rover/ and integrate the Mate tools https://code.google.com/archive/p/mate-tools/wikis/ParserAndModels.wiki into their chat bot

[5]Data sets change frequently and are chosen from commonly used and publicly available sources, e.g. a subset of the 20 Newsgroups data at http://qwone.com/~jason/20Newsgroups/ or a subset of the Movie Review Dataset at https://ai.stanford.edu/~amaas/data/sentiment/.

5 A Sample Class Session

We now exemplify the CBL method using a class from the Communication segment on dialogue and chat bots, meant for a double session of 2x90 minutes. Table 1 shows the individual components, which we will now discuss one by one.

The class begins with a short, ca. 15 minute introduction to human-machine dialogue followed by an ungraded self-test (administered through the Learning Management System) that is intended to tell students whether they caught all the important concepts or whether they should follow up on some topics, using the lecture slides or asking the professor, before moving on.

In general, the self-tests in CBL give feedback to students about their learning, but also show the professor which concepts larger groups of students may still be unsure of. This helps the professor to address the problem efficiently and quickly by giving a short additional explanation targeted to the exact area of difficulty. Self-tests are ungraded in the AI class in order to stress their informational character.

Once the students are satisfied that they understood the concepts from the introduction, they start on a self-study period by watching a video on the next content input (about human-human dialogue). Students are able to speed up or slow down the video as needed, which is not possible in a live lecture. At this point, students' progress through the materials starts to de-synchronize as some take more time than others on individual tasks.

The video input is followed by two exercises: One on the use of adjacency pairs and evidence of Gricean Maxims (Grice, 1975) in everyday conversations, and an implementation task that asks students to expand the tiny chat bot with correct reactions to e.g., greetings. During this time, the professor is available for questions and discussion. Ideally, the professor cycles through the room during this time in order to be easily available and to lower the threshold for asking for help. This also helps the professor assess the general progress of the class and makes it easier to identify students who work fast and might enjoy an extra challenge or input and students who are struggling.

After the active work on exercises, students switch back to passive mode and watch a video on the technical framework behind automated voice assistants. Students learn about identifying user intentions through matching keywords from the in-

Topic	Activity Format	Work Strategy
Human-machine dialogue	Lecture	Group/Passive
	Self-test	Individual/Active
Human-human dialogue	Video	Individual/Passive
Adjacency pairs and Gricean Maxims	Exercises	Individual/Active
Implementing Adjacency pairs in the chat bot	Exercise	Individual/Active
Automated voice assistants	Video	Individual/Passive
Demo of voice assistant	Lecture	Group/Passive
Intents and skills in the chat bot	Exercise	Pairs/Active
Realistic chat bots	Online Course	Individual/Voluntary

Table 1: Activities in a sample CBL class on Dialogue.

put to *intent* definitions and triggering the matching *skill* to fulfil the request.

This is followed by an interactive live demo of *Mycroft*[6], the sample assistant presented in class. The timing of the group activity can be difficult since student progress is often heterogeneous at this time, but the demo does not presuppose completion of the voice assistant video, so this activity can be paused for the demo.

Finally, the students are asked to use their new knowledge about intents and skills to further extend their chat bot. This task is done in pairs or small groups. One reason for this is to provide variation to the individual work; another reason is didactical: Part of the exercise is the definition of keywords that the chat bot should use to identify the intention of the user (formalised as the *intent*). Students are asked to define their own keywords first and then compare to their partners' solution. For many students, this is an eye-opener to the amount of paraphrase and variation present in natural language interactions. Students are asked to define an intent and the corresponding keywords only, but some students enjoy integrating external APIs and actually implementing the corresponding skill, as well.

With this activity, the class proper is finished. Students who enjoy working on the chat bot are pointed to an external on-line teaching resource[7] that takes them through the construction of a larger chat bot step by step, expanding on the topics covered in the class.

This sample class demonstrates the interleaving of live lectures, video input, self-tests and exercises in CBL. Students regularly switch from active to passive learning modes and from individual to group work while the professor is available for individual interactions as needed. Professors can flexibly add more in-presence lecture phases since they can quickly identify concepts that remain difficult for many students through the self tests. Otherwise, professors' time is mostly spent in individual discussions with their students, which helps them address the heterogeneity of their students' backgrounds efficiently.

6 Student and Professor Perspective

We now go on to report student feedback from a survey taken by CS students in the AI class.

6.1 Structured Feedback by Students

At the end of the semester, we asked the students to complete a survey with a total of 29 questions. Our goal was on the one hand to hear about technical problems with the ressources or issues with the content that had not yet come up. On the other hand, we were interested in the students' reaction to the teaching method. Given the sequence of different activities for each class, we were concerned that students might find it difficult to identify the overarching theme of the classes. Another concern was the use of video inputs, since in the aftermath of pandmic-related on-line teaching students commented that they were fed up with recorded content. Therefore, we wanted to know whether the students felt they were getting appropriate amounts of interaction with their professor given the large amount of self-study activities and whether they were able to focus during the vidoes. Finally, we asked whether the students felt prompted to dig deeper into the materials by the test and exercise activities, as intended by the method.

Fig. 1 shows the results of the survey, omitting questions on technical and content quality. 22 students (41% of the total number of actively participating students) took part in the on-line survey, which was announced in class and by email.

We find that students overwhelmingly reported

[6] https://mycroft.ai/get-started/

[7] https://ki-campus.org/courses/conversational-ai

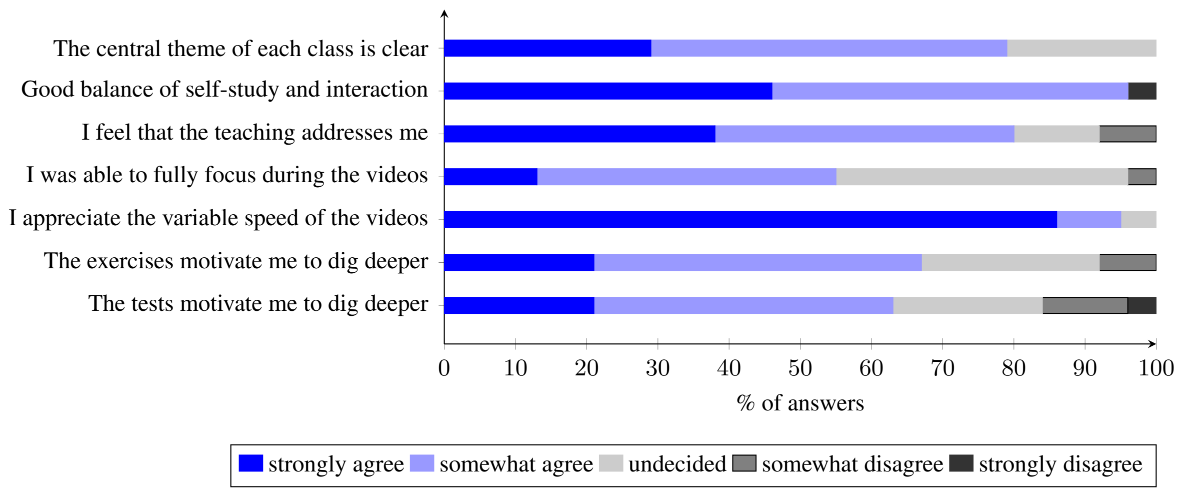

Figure 1: Student feedback on CBL from third-semester CS students. $N = 24$, or 42% of enrolled students.

no or few issues identifying the overall theme of all the activities in a class (21% were undecided). They were therefore able to follow the train of thought of the materials.

Students were very or at least somewhat satisfied with the balance between self-study and interaction with the professor. 4% or two out of 22 students however strongly disagreed, indicating some potential for polarization. Similarly, 80% of students felt personally addressed by the teaching method, while the rest were undecided or somewhat disagreed. Overall, it appears that the method appealed to the majority of students, but there was a small and vocal group that disliked the approach. We do not have numbers for comparison to other teaching methods like lectures or classic tutorial sessions for comparison, unfortunately.

Regarding the use of videos, almost half of students report that they found it hard to fully focus on the input. Again, we have no comparison to a traditional lecture to gauge how much of this issue is due to the frontal lecture paradigm and how much is due to the specific CBL setup where the students' neighbors may simultaneously be working on other activities. We also include an intriguing piece of feedback on the video materials: Students greatly appreciate the possibility of speeding up the video replay, something that is not possible in a traditional lecture, of course. This encourages us to overall recommend the continued use of videos in CBL (over live lecture inputs, which are also hard to time as the class proceeds).

Finally, the self-test feedback and exercises motivated the majority of students to engage more deeply with the learning materials. Feedback on the tests is more contentious than on the exercises, which may be due to the nature of the self-tests: They were intended as a quick way of checking whether students remembered the main points of the lecture and video inputs and may therefore have been too easy to be challenging for the majority of engaged learners. We plan to experiment with the use of adaptive testing for the feedback tests in order to present each student individually with questions that are appropriate for their level.

The relatively low participation in the survey (of less than 50% of the students who actively participate in the class) correlates with attendance and may be explained by a tendency of students to choose different times and places to work through the material, even if the professor is not available then. After a week, the tests and exercises routinely show more active users than students were present in class. We see this as a further advantage of the method, since it offers flexibility to students and allows them to work independently, taking charge of their own learning goals despite the usually highly structured HAW study programs.

In sum, the picture is positive: students feel addressed personally through CBL and feel motivated to engage with the materials by the self-tests and exercises. Even though the method was developed for beginning students, students in the middle of their study program also appreciate CBL and its advantages (for example, the variable speed of videos or the option of working through the materials whenever and wherever convenient). We did not see students confused by the large number of activities per class or feeling left on their own with self-study activities. Students did, however, report that they had a hard time focussing on the videos, so these will be revised for length and conciseness. Overall, we conclude that CBL is an appropriate method for teaching CL content to a heterogenous set of students. We now go on to further demonstrate the versatility of CBL by feedback from students in the very first and last semesters of their study programs.

6.2 Structured Feedback from Other Classes

When transferring CBL from first-semester courses in Mathematics to CS topics, we also expanded to classes from other phases of the study program: AI (as just discussed Section 6.1) in the third semester and a class on Machine Learning in students' final semester. We collected structured feedback from all three courses using the same questionnaire in order to be able to compare students' impressions and see how well the method adapts to the different needs of students at different points in their studies.

Fig. 2 shows the feedback from the first-semester students (Civil Engineering program, Mathematics class) at the top and the feedback from the final-semester students (CS, Machine Learning) at the bottom. In the middle, we repeat the feedback from the third-semester AI students (cf. Section 6.1) for comparison.

Our first finding is that students in all phases of study are generally satisfied with CBL: in every group, at least 75% of students strongly agree or somewhat agree with the first three of our feedback propositions. Students in higher semesters are at least as satisfied as first-semester students, for whom the method was developed. This is proof of the versatility of the method and ties in well with earlier findings (Knebusch et al., 2019).

Additionally, interesting patterns emerge across semesters: As students progress in their studies, they have an easier time identifying the central theme of each class and are more satisfied with the mix of self-study and interaction in CBL. They also feel more personally addressed by the teaching method (evidenced by far less disagreement with our third proposition and a higher percentage of strong agreement with it). We interpret this as a sign of students' increased experience with the HAW learning environment and better self-directed learning skills. More experienced students are more comfortable during self-study than the inexperienced first-semester students, and also report an easier time focusing on the videos as the semesters progress. They seem to have developed more sophisticated strategies for dealing with video materials, as the third-semester and higher students express much more appreciation for the variable video speeds than the first semester students.

The final two feedback propositions ask about the exercises and tests. Here, the third-semester AI students are least motivated by the exercises, possibly because they also complete a group project for their class, which does not exist in the first-semester Mathematics class and which is larger than the corresponding Machine Learning group project. At the same time, the results are reason to scrutinize the AI materials more closely. The large positive impact of the tests for the first-semester students in Mathematics can be explained by the more challenging nature of the tests in their class (cf. Section 6.1).

In sum, we find that students from all phases of study appreciate CBL, but we see that the increased self-study skills of higher-semester students serve them well. The participation rate in the feedback speaks a similar language: 78% of first-semester students participated, but only about 40% of students in higher semesters. This is correlated with attendance rates (although all students were invited to participate) and demonstrates that students in later semesters appreciate the option of using the CBL materials entirely for self-study. We conclude that CBL can be flexibly used for classes throughout a study program, since it offers guidance to inexperienced students and flexibility to advanced students in addition to maximising individualized learning and individual interaction with the professor if desired.

6.3 Impressions from Professors

The authors have taught the above-mentioned classes using CBL. Our informal observations on CBL classes are very positive. Students are engaged and active during the whole of class, and much more so than during traditional lectures or even the introductory lecture part. During exercises, often small groups form spontaneously as students explain the tasks to each other and discuss them. The atmosphere in class is very focused and students rarely engage in non-class related activities even in 2x90 minute segments.

We also appreciate the opportunity to interact with individual students and discuss difficult issues face-to-face instead of lecturing to a group. The

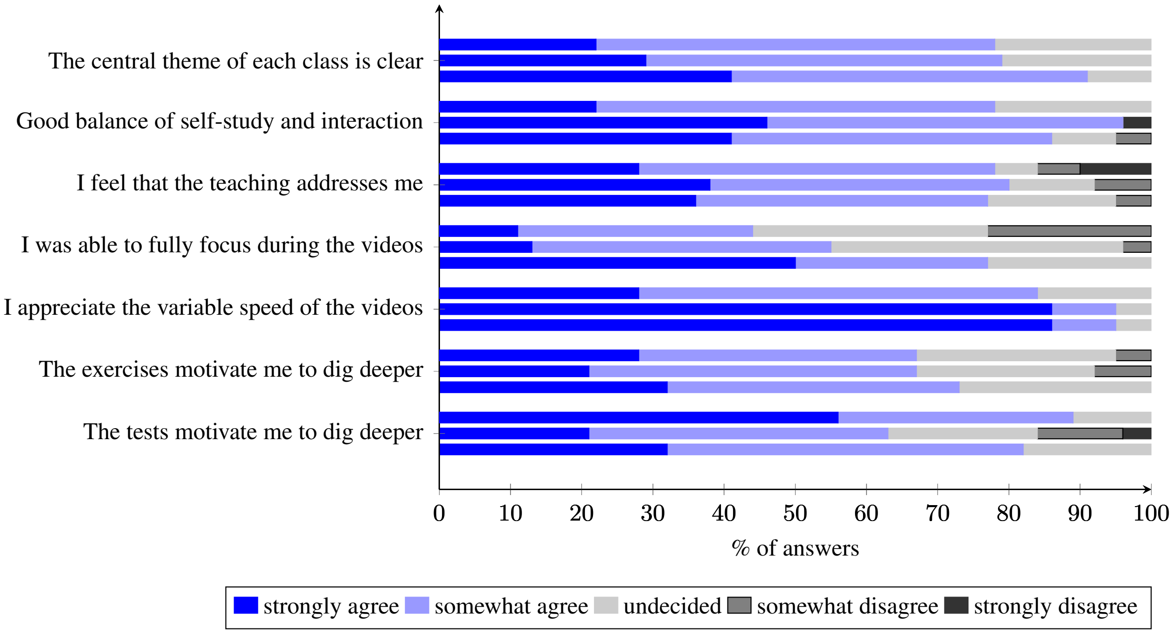

Figure 2: Student feedback on CBL. Top: First-semester Civil Engineering students in Mathematics ($N = 18$, or 78% of enrolled students.), middle: third-semester CS students in AI ($N = 24$, or 42% of enrolled students), bottom: final-semester CS students in Machine Learning ($N = 22$, or 41% of enrolled students).

self-study activities in CBL also free up time for more in-depth discussions with students who already have some experience with the class topic and who otherwise might be bored by the materials and disengage with the class.

7 Conclusions

We have presented the adaptation of the CBL method (Knebusch et al., 2019) to teaching CL content to CS students on the Bachelor's level. CBL encourages self-study in the presence of the professor, who is available for questions and discussions. It therefore helps to address heterogeneity in students' educational backgrounds and previous experience, frees up professors to interact with individual students and provides students with a large amount of hands-on exercises.

Structured feedback from students show that they feel personally addressed by the method and appreciate the balance between self-study and interaction with the professor. The materials motivate them to deeply engage with the learning materials and they appreciate the ability to e.g. choose the speed of input videos according to their needs.

The structured feedback from first-semester, third-semester and final-semester students also demonstrates that all groups profit from CBL, while the more experienced students make use of the flexibility afforded by the focus on self-study. Anecdotal evidence from professors shows consistent student engagement with the materials and the ability to cater to individual students, be they struggling or advanced.

In sum, we present evidence that the method is very suitable for teaching with a focus on addressing heterogeneity in different study programs and at various stages during study programs. We therefore believe that the method has proven its versatility and can be used in other academic settings where heterogeneity is present in the student body - for example teaching CL to groups made up of students from various fields.

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