Beyond the Textbook: Rethinking Students‘ Competencies in the LLM Era

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Event: Generative AI: Implications for Teaching and Learning

Agenda

1.) Introduction

2.) Related Work

3.) Performance of Large Language Models in Introductory Programming Tasks

4.) Feedback Provided by Large Language Models

5.) Implications on Students‘ (and Educators‘) Competencies

6.) Discussion and Conclusions

7.) Future Work

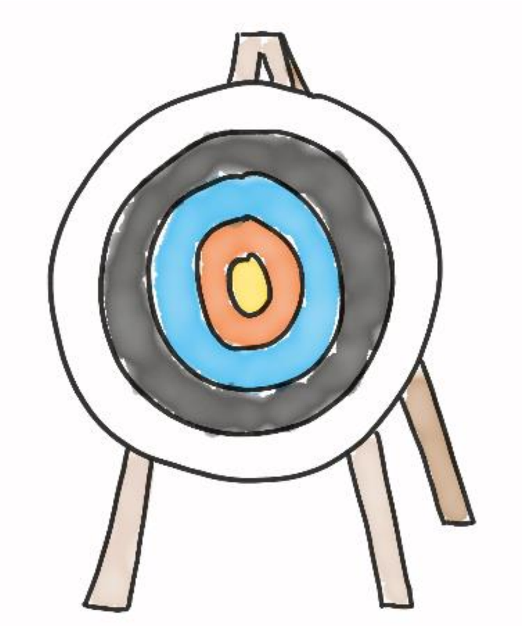
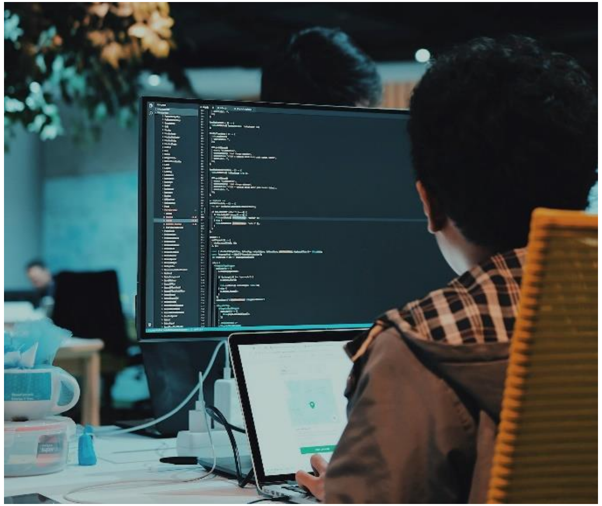


Illustration: Alexander Sperl

Introduction

- Challenges in Introductory Programming Education are manifold
  - Increasing student numbers
  - Limited staff resources
  - Heterogeneous learner groups
  - Need for formative feedback
- Growing demand for automated teaching support, while current learning environments are limited (Jeuring et al. 2022)
- Introduction of ChatGPT in late November 2022 as easily accessible, powerful tool
- Promising performance, code explanation, and error analysis in introductory programming tasks (Finne-Ansley et al. 2022, 2023)

➔ Need to explore the potential of LLMs in Computing Education



Related Work

LLMs have become subject to research, e.g.,

- Performance of OpenAI’s Codex in CS 1 and CS 2 tasks (Finnie-Ansley et al. 2022, 2023)
- Educational opportunities and challenges of LLMs (Becker et al. 2023)
- Investigating student learning with and without LLMs (Kazemitabaar et al. 2023)
- Application of LLMs to generate exercises (Sarsa et al. 2022) and code explanations (MacNeil et al. 2022)
- Exploration of prompt engineering, how to phrase questions (Denny et al. 2023)
- ITiCSE working group on curiccula, learning objectives, pedagogy, ethics, educators‘ and students‘ perceptions, and many other aspects (Prather et al. 2023)

➔ There are still many open questions, and few classroom experiences!

Performance of LLMs in Introductory Programming Tasks

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Goals and Research Questions:

- Exploring the performance of ChatGPT-3.5 (May 24) and GPT-4 when solving introductory programming tasks; and discuss implications for higher education and assessments
- RQ: How does an LLM like ChatGPT solve introductory programming tasks?

Method:

- Selection of all 72 CodingBat Python tasks, Requesting ChatGPT (3.5 and GPT-4) to generate a solution (by using the task and input)
- Evaluating the outputs‘ quality via CodingBat (i.e., unit tests)

Results:

- Summary of ChatGPT-3.5‘s and GPT-4‘s performance in 72 introductory programming tasks (from CodingBat)

Performance of LLMs in Introductory Programming Tasks

python Copy code

```python
def alarm_clock(day, vacation):
    # Check if on vacation
    if vacation:
        # If on vacation, check if weekend
        if day == 0 or day == 6:
            return 'off'  # 'off' on weekends during vacation
        else:
            return '10:00'  # '10:00' on weekdays during vacation
    else:
        # If not on vacation, check if weekend
        if day == 0 or day == 6:
            return '10:00'  # '10:00' on weekends
        else:
            return '7:00'  # '7:00' on weekdays
```

Performance of LLMs in Introductory Programming Tasks

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Given a day of the week encoded as 0=Sun, 1=Mon, 2=Tue, ...6=Sat, and a boolean indicating if we are on vacation, return a string of the form "7:00" indicating when the alarm clock should ring. Weekdays, the alarm should be "7:00" and on the weekend it should be "10:00". Unless we are on vacation -- then on weekdays it should be "10:00" and weekends it should be "off".

alarm_clock(1, False) → '7:00'
alarm_clock(5, False) → '7:00'
alarm_clock(0, False) → '10:00'

Go ...Save, Compile, Run (ctrl-enter)

```
def alarm_clock(day, vacation):
    if vacation:
        if day >= 1 and day <= 5:  # Weekdays
            return '10:00'
        else:  # Weekends
            return 'off'
    else:  # Not on vacation
        if day >= 1 and day <= 5:  # Weekdays
            return '7:00'
        else:  # Weekends
            return '10:00'
```

Expected	Run		
alarm_clock(1, False) → '7:00'	'7:00'	OK	
alarm_clock(5, False) → '7:00'	'7:00'	OK	
alarm_clock(0, False) → '10:00'	'10:00'	OK	
alarm_clock(6, False) → '10:00'	'10:00'	OK	
alarm_clock(0, True) → 'off'	'off'	OK	
alarm_clock(6, True) → 'off'	'off'	OK	
alarm_clock(1, True) → '10:00'	'10:00'	OK	
alarm_clock(3, True) → '10:00'	'10:00'	OK	
alarm_clock(5, True) → '10:00'	'10:00'	OK	
other tests		OK	

All Correct

next | chance

Python > Logic-1

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Code is saved so long as this session is active. Create an account above to save code past this session.

Performance of LLMs in Introductory Programming Tasks

CodingBat task area	GPT-3.5 textual explanation	GPT-3.5 program code	GPT-3.5 correct unit test results	GPT-4 textual explanation	GPT-4 program code	GPT-4 correct unit test results
Warmup-1	11/12	12/12	12/12	12/12	12/12	12/12
Warmup-2	9/9	9/9	9/9	9/9	9/9	9/9
String-1	11/11	11/11	10/11	11/11	11/11	11/11
List-1	12/12	12/12	12/12	11/12	12/12	12/12
Logic-1	8/9	9/9	8/9	9/9	9/9	9/9
Logic-2	7/7	7/7	6/7	6/7	7/7	6/7
String-2	6/6	6/6	6/6	6/6	6/6	4/6
List-2	6/6	6/6	6/6	6/6	6/6	5/6

Results (excerpt):

- GPT-3.5 solves 69 of 72 tasks on the first attempt (95,5%), GPT-4 68 of 72 tasks (94,4%) (Kiesler and Schiffner 2023)
- Problems where the LLM did not succeed on first attempt contained, e.g., syntactic ambiguity
- Disclaimer: LLMs may have been trained on the model solutions, and tasks were well described.

Feedback Provided by Large Language Models

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Goals and Research Questions:

- Exploration of generative AI (ChatGPT as LLM) to generate formative feedback in response to students' solutions to introductory programming tasks.
- RQs: What output is generated by an LLM like ChatGPT in response to a beginner student help request? How can we characterize the output in terms of feedback?

Method:

- Selection of four tasks and submissions to weekly exercises (from week 1-4 of a CS1 class, 300 students)
- Design-based Research, iterative approach, exploration of prompts („What's wrong with my code?"), 3 regenerated answers (March 23)
- Development of inductive categories to characterize the output of the feedback

Results (excerpt):

- Overview of criteria to characterize the output generated by ChatGPT (e.g., Content, Quality, Other)

Feedback Provided by Large Language Models

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Results (excerpt):

- Table with characterization of ChatGPT's responses to students' help request with students' solution (Kiesler, Lohr, Keuning 2023)

Symbol	Meaning
INFO	Requesting more information
STYLE	Stylistic suggestion
CAUSE	Textual explanation cause of error
FIX	Textual explanation fix of error
CODE	Code provided
EXA	Illustrating examples
COMP	Code, if provided, compiles
MIS	Misleading information
UNC	Uncertainty
META	Meta-cognitive elements
MOT	Motivational elements

	CONTENT																		QUALITY									OTHER					
	INFO			STYLE			CAUSE			FIX			CODE			EXA			COMP			MIS			UNC			META			MOT		
Stud_task	R1	R2	R3	R1	R2	R3	R1	R2	R3	R1	R2	R3	R1	R2	R3	R1	R2	R3	R1	R2	R3	R1	R2	R3	R1	R2	R3	R1	R2	R3	R1	R2	R3
01_TEOS	○	○	○	○	○	○	○	●	●	○	○	○	●	◐	●	○	○	○	●	–	●	○	●	●	○	○	○	○	○	○	○	○	○
02_TEOS	○	○	○	●	●	●	●	●	●	●	●	●	●	●	●	○	○	○	●	●	●	●	●	○	○	○	○	○	○	○	○	○	○
03_TEOS	○	●	○	○	○	○	●	●	●	●	●	●	◐	○	○	○	○	○	–	–	–	●	○	○	○	○	○	○	○	○	○	○	○
04_TEOS	○	○	○	○	●	○	○	○	○	○	○	○	○	○	○	○	○	○	–	–	–	○	○	○	●	●	●	●	●	●	○	○	○
05_TEOS	○	○	○	●	●	●	●	●	●	●	●	●	●	●	●	○	○	○	●	●	●	○	○	○	○	○	○	○	○	○	○	○	○
06_TEOS	○	○	○	●	○	●	●	●	●	●	●	●	◐	●	◐	●	●	●	–	●	–	○	○	○	○	○	○	○	○	○	○	○	○
07_TEOS	○	○	○	○	○	○	●	●	●	●	●	●	●	●	○	○	○	○	●	●	–	○	●	○	○	○	○	○	○	○	○	○	○
08_TEOS	○	○	○	○	●	○	●	○	●	●	●	●	◐	○	○	○	○	○	–	–	–	○	○	○	○	○	○	○	○	○	●	○	○
09_TEOS	○	○	○	○	●	○	●	●	●	●	●	●	●	●	●	○	○	○	●	●	●	●	●	●	○	○	○	○	○	○	○	○	○
10_TEOS	○	○	○	○	●	○	●	●	●	●	●	●	●	●	●	○	○	○	○	●	●	●	○	○	○	○	○	○	○	○	○	○	○
01_TTBS	○	○	○	○	○	○	●	●	●	○	●	●	○	●	●	○	●	○	–	●	●	●	○	○	●	○	○	○	○	○	○	○	○
02_TTBS	○	○	○	○	○	○	●	●	●	●	●	●	●	●	●	○	○	●	–	●	●	○	○	○	○	○	○	○	○	○	○	○	○
03_TTBS	○	○	●	○	●	●	●	○	●	●	○	○	●	○	○	○	○	○	●	–	–	●	○	●	○	○	●	○	○	○	○	○	○
04_TTBS	○	○	○	○	○	○	●	●	●	●	●	●	●	◐	●	○	○	○	●	●	–	○	○	●	○	○	○	○	○	○	○	○	○
05_TTBA	○	○	○	○	○	●	●	●	●	●	●	●	◐	●	●	○	●	○	–	●	●	○	●	●	○	○	○	○	○	○	○	○	○
06_TTBA	○	○	○	●	○	○	●	●	●	●	●	●	○	●	◐	○	○	○	–	●	–	●	●	●	●	○	○	○	○	○	○	○	○
07_TTBA	○	○	○	●	●	○	●	●	●	●	●	●	○	◐	◐	○	○	●	–	–	–	●	●	●	○	●	○	○	○	○	○	○	○
08_TTBA	○	○	○	○	○	○	●	●	●	●	●	●	●	●	●	●	○	●	●	○	●	●	●	●	○	○	○	○	○	○	○	○	○
09_TTBA	○	○	○	○	○	○	●	○	●	●	●	●	●	●	●	○	○	○	●	●	●	●	○	●	○	○	○	○	○	○	○	○	○
10_TTBA	○	○	○	○	○	○	●	●	●	●	●	●	●	●	●	●	○	○	●	●	●	●	●	●	○	○	○	○	○	○	○	○	○
01_NEGF	○	○	○	○	●	●	●	○	●	●	○	●	●	○	○	●	○	○	●	–	–	●	○	●	○	●	●	○	●	○	○	○	○
02_NEGF	○	○	○	○	○	●	●	●	●	●	●	●	●	●	○	○	○	○	●	●	–	●	●	●	○	○	●	○	○	○	○	○	●
03_NEGF	○	○	○	○	○	●	●	●	●	●	●	●	●	●	●	○	○	○	●	●	●	●	●	●	○	○	○	○	○	○	●	○	○

Implications on Students‘ and Educator‘s Competencies

Students‘ Competencies (which we implicitly expect):

- Students need to understand the task description.
- Students need to be able to express implicit side conditions/restrictions by the educator in their own words.
- Students need to analyze and evaluate the output generated by the LLM (more than understanding!):
  - Students have to trace code.
  - Students have to predict the outcome of the generated code.
  - Students have to test the generated code.
  - Students have to evaluate the adequacy of the output w.r.t. correctness (e.g., if it compiles) and style
  - Students have to evaluate the adequacy of the output w.r.t. the task and other limitations.
- Students may have to integrate the generated solution (e.g., code snippet) into their own code.
- Students need to develop adequate (follow-up) prompts.

Implications on Students‘ and Educator‘s Competencies

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Implications on Educators‘ Competencies:

- Educators need to formulate tasks adequate for novices (without ambiguity), and transparently communicate their expectations.
- Educators need to know the basic principles of how LLMs generate textual output including code.
- Educators need to know the limitations for LLMs like ChatGPT and their (rapidly increasing) potential to solve programming tasks.

Other aspects:

- Educators need to be open to change, i.e. adapt to this new, ubiquitous tool.
- Educators need to acknowledge the existence of this tools in their classroom.
- Educators need experience in using LLMs themselves.

Discussion and Conclusions

- ChatGPT can solve well-known introductory programming tasks.
- ChatGPT has the potential to address learners' informational needs.
- ChatGPT offers more types of feedback than other learning environments (Jeuring et al. 2022).

- **BUT:**
  - The output greatly varies depending on prompts, and misleading information for novices is contained.
  - Educators need to support students using these tools, and should not ignore them.
  - Will we see a shift towards student-centered teaching, learning, and assessment?
  - Will we put more emphasis on understanding (i.e., "reading" or "talking about") code instead of checking the produced code?
  - How can we prepare students ideally to use LLMs?

Future Work

- Open research questions to address:
  - How can we reduce the misleading information provided by ChatGPT and LLMs?
  - How can we manipulate prompts to receive a certain type of feedback? (work-in-progress)
  - How can we guide students and train educators to safely use LLMs?
  - To what extent can LLMs help broaden participation in CS or programming?
  - How accessible is this technology?

Tack för din uppmärksamhet!

Literature

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