CogGen: A Learner-Centered Generative AI Architecture for Intelligent Tutoring with Programming Videos

Wengxi Li[1][0009−0003−1876−6303], Roy Pea[2][0000−0001−6301−3536], Nick Haber[2][0000−0001−8804−7804], and Hariharan Subramonyam[2][0000−0002−3450−0447]

[1] City University of Hong Kong, Hong Kong SAR, China
`wengxili@cityu.edu.hk`
[2] Stanford University, Stanford, California, United States
`{roypea,nhaber,harihars}@stanford.edu`

Abstract. We introduce CogGen, a learner-centered AI architecture that transforms programming videos into interactive, adaptive learning experiences by integrating student modeling with generative AI tutoring based on the Cognitive Apprenticeship framework. The architecture consists of three components: (1) video segmentation by learning goals, (2) a conversational tutoring engine applying Cognitive Apprenticeship strategies, and (3) a student model using Bayesian Knowledge Tracing to adapt instruction. Our technical evaluation demonstrates effective video segmentation accuracy and strong pedagogical alignment across knowledge, method, action, and interaction layers. Ablation studies confirm the necessity of each component in generating effective guidance. This work advances AI-powered tutoring by bridging structured student modeling with interactive AI conversations, offering a scalable approach to enhancing video-based programming education.

Keywords: Cognitive Apprenticeship · Large Langauge Models · Student Modeling · Conversational Agents

1 Introduction

Video has emerged as a preferred medium for learning programming. According to a recent Stack Overflow survey, developers who learned through "How-to-videos" and "Video-based E-Courses" accounted for 54.2% and 49.9%, respectively [3]. Regardless, the most effective learning paradigm for programming videos is *learning by doing* [4]. However, practicing coding tasks while watching videos is difficult for novices, requiring clear instructions and immediate feedback [1].

Learning to program requires integrating multiple skills: understanding syntax, grasping programming concepts, and applying problem-solving strategies [9]. *Instructional Design Principles* guide how these learning experiences should be structured [7]. The Cognitive Apprenticeship (*CogApp*) framework addresses

[3] https://survey.stackoverflow.co/2024/developer-profile#learning-to-code

these needs by making expert programmers' thought processes visible to novices through six teaching moves: Modeling, Coaching, Scaffolding, Articulation, Reflection, and Exploration [6]. This framework emphasizes guided practice with gradual transfer of responsibility to learners, effectively managing cognitive load through step-by-step instruction [19, 2, 14].

While large language models (LLMs) have shown promise in programming education [10, 11], they present several challenges: they tend toward verbose responses [21, 5], struggle to maintain focus in multi-turn conversations [18, 16], and lack structured approaches for step-by-step teaching [15, 17].

To address these gaps, we developed *CogGen*, a systematic architecture that ensures controlled and relevant message generation tailored to students' specific learning needs based on the *CogApp* framework. *CogGen* operates by first segmenting programming videos into distinct learning goals, then selecting appropriate teaching methods from the *CogGen* framework based on an internal student model for each learning goal. In summary, our key contributions include:

1. *CogGen*: A pipeline for generating learning conversations, using a domain-specific language to organize *CogApp* methods, enabling LLMs to deliver guidance that is both consistent and personalized.
2. Technical evaluation demonstrating *CogGen*'s effectiveness in generating structured and controlled instruction via LLMs, with evidence that each component plays a necessary role in achieving this performance.

2 *CogGen* Architecture

CogGen implements a set of LLM prompting techniques that yield conversational utterances grounded in the *CogApp* framework. The architecture consists of (1) a video segmentation module that *slices* long videos based on learning goals using a prompt chaining approach, (2) a DSL generator that produces the *context* for the LLM to generate utterances in interaction with the learner, and (3) a student model to capture the student's learning progress and inform appropriate mentor *moves*. Here, we provide technical details about each module and data representations to make the generated conversations *consistent* and *controllable*. We use few-shot prompting with GPT-4 (temperature=0.3) for all the modules.

2.1 Video Segmentation by Learning Goals

When segmenting video transcripts, small references to unrelated goals can cause misclassification. Our approach minimizes this through a three-step process: (1) *Summarize* key points for each learning goal; (2) *Retrieve* transcript sentences aligning with these summaries; (3) *Rearrange* segments based on timestamps.

2.2 Instructional Prompt Generator

For each video segment, we generate a teaching plan that aligns with the *CogApp* framework. Our prompting pipeline follows three consecutive steps:

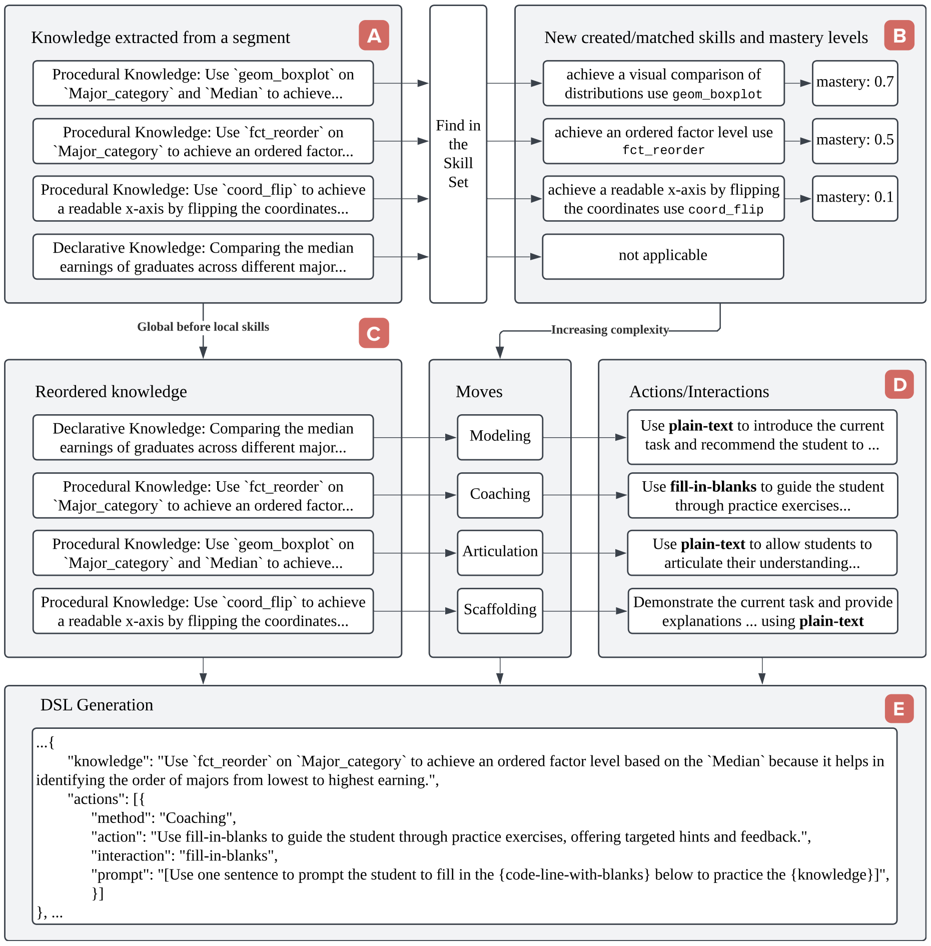
Table 1. Representations of the two types of knowledge in *CogGen*. The bold parts are later used in the student model.

Knowledge	**Representation**	**Example**
	Concept Related	
Declarative	[Subject] + [verb phrase] + that + [independent clause].	*The median income by college major shows that majors earn a median income of over $30K right out of college.*
Procedural	To achieve/understand + [specific goal/outcome] + one must + **[actions/processes]** + [additional details] + considering/using + [relevant factors/tools].	*To understand the distribution of earnings by college major, one must* ***examine the histogram and identify overall trend or extreme values****, considering whether high earnings are due to the field's financial reward.*
	Programming Related	
Declarative	The task is + [final goal] + using + [general method/tool] + and + [additional method/technique for enhancement].	*The task is comparing the distribution of median earnings across different major categories using a box plot and adjusting the visualization for better readability and interpretation.*
Procedural	To achieve + **[specific goal]** + one must + **[action/verb]** + **[specific tool/method]** + on + [object/target] + because + [reason/purpose].	*To* ***achieve an ordered factor level*** *based on the 'Median', one must* ***use 'fct_reorder'*** *on 'Major_category', making it easier to compare distributions.*

First, we use few-shot prompts to extract procedural and declarative knowledge from the segmented transcripts using standardized formats (Figure 1A and Table 1). For example, procedural knowledge follows patterns like "To achieve [specific goal] one must [action/verb] [specific tool/method] on [object/target] because [reason/purpose]." This structured approach enables mapping to the student model and ensures consistent generation of conversational messages.

Second, we apply three principles to select proper teaching methods [6]: (1) global before local skills, prioritizing conceptual overviews before detailed tasks; (2) increasing complexity, adapting instruction to student mastery levels; and (3) increasing diversity, varying task types to maintain engagement.(Figure 1B&C)

Finally, we generate a domain-specific language (DSL) that integrates knowledge summaries, pedagogical moves, and context to produce structured interactions (Figure 1D&E). Each move (e.g., Modeling, Scaffolding) is mapped to specific actions and interaction types, which are used to generate *prompts* that guide the conversation. The prompts are stored in a queue, the head of which is used to produce the next message. This approach ensures interactions remain focused on the video content while following the intended pedagogical sequence.


Knowledge extracted from a segment
A
Procedural Knowledge: Use `geom_boxplot` on `Major_category` and `Median` to achieve...
Procedural Knowledge: Use `fct_reorder` on `Major_category` to achieve an ordered factor...
Procedural Knowledge: Use `coord_flip` to achieve a readable x-axis by flipping the coordinates...
Declarative Knowledge: Comparing the median earnings of graduates across different major...
Find in the Skill Set
New created/matched skills and mastery levels
B
achieve a visual comparison of distributions use geom_boxplot
mastery: 0.7
achieve an ordered factor level use fct_reorder
mastery: 0.5
achieve a readable x-axis by flipping the coordinates use coord_flip
mastery: 0.1
not applicable
Global before local skills
C
Increasing complexity
Reordered knowledge
Declarative Knowledge: Comparing the median earnings of graduates across different major...
Procedural Knowledge: Use `fct_reorder` on `Major_category` to achieve an ordered factor...
Procedural Knowledge: Use `geom_boxplot` on `Major_category` and `Median` to achieve...
Procedural Knowledge: Use `coord_flip` to achieve a readable x-axis by flipping the coordinates...
Moves
Modeling
Coaching
Articulation
Scaffolding
Actions/Interactions
D
Use **plain-text** to introduce the current task and recommend the student to ...
Use **fill-in-blanks** to guide the student through practice exercises...
Use **plain-text** to allow students to articulate their understanding...
Demonstrate the current task and provide explanations ... using **plain-text**
DSL Generation
E

```
...{
    "knowledge": "Use `fct_reorder` on `Major_category` to achieve an ordered factor level based on the `Median` because it helps in
identifying the order of majors from lowest to highest earning.",
    "actions": [{
        "method": "Coaching",
        "action": "Use fill-in-blanks to guide the student through practice exercises, offering targeted hints and feedback.",
        "interaction": "fill-in-blanks",
        "prompt": "[Use one sentence to prompt the student to fill in the {code-line-with-blanks} below to practice the {knowledge}]",
        }]
}, ...
```

Fig. 1. Details of the *CogGen* architecture: (A) extracting procedural knowledge and declarative knowledge from the video segment, (B) the knowledge is mapped to skills and mastery levels, (C) using the principles to reorder the knowledge and decide moves for each knowledge, (D) moves are mapped to actions and interactions, (E) knowledge, moves, actions, interactions, and prompts are integrated to form the DSL.

2.3 Student Performance Monitoring

To adapt instruction based on student performance, we implement a Bayesian Knowledge Tracing (BKT) framework that tracks skill proficiency [3, 13]. Each knowledge component extracted from video segments is translated into a corresponding student skill (e.g., "achieve an ordered factor level use `fct_reorder`").

Skill proficiency levels are initialized based on the student's estimated mastery of the current learning goal (default 0.1). As students interact with the system, BKT parameters are dynamically updated to reflect evolving proficiency.

When students encounter previously practiced knowledge, we use semantic similarity [12] to identify relevant skills and update their parameters. The parameters are stored between learning sessions to maintain continuity across videos.

This integrated approach allows CogGen to select appropriate teaching methods based on current student mastery, providing scaffolding for low-mastery skills and encouraging articulation for higher-mastery skills, creating a personalized learning experience that adapts to individual student needs.

3 Evaluation

To evaluate *CogGen*'s effectiveness across diverse learning scenarios, we selected three distinct programming video lesson topics: Exploratory Data Analysis (EDA), Machine Learning (ML), and Game Development. We evaluated the architecture using three metrics: (1) segmentation accuracy, (2) controllability of generated content, and (3) component importance through ablation studies.

3.1 Procedure

Two experts with experience in educational video analysis served as annotators for segmenting videos according to learning goals. For segmentation evaluation, we compared timestamps between manually labeled segments and those generated by LLM, using a five-second error threshold to account for differences between continuous video viewing and discrete transcript processing.

For the controllability evaluation, we created a hierarchical classification scheme based on the prompt pipeline. The system-generated data were extracted from DSL files, which defined expert-specified teaching methods. Three domain experts independently labeled 277 dialogue messages in six videos (124 EDA, 89 ML, and 64 Game Development utterances). We compared labeled data with system-generated data using precision, recall, and F1-score metrics.

To evaluate the component importance of *CogGen*, we compared four conditions: (1) *Baseline*, unconstrained generation using only video segments; (2) *Knowledge-Only*, which summarizes segment knowledge without *CogApp* theory; (3) *Method-Only*, which uses *CogApp* theory without specific knowledge awareness; and (4) *Full* condition with the complete pipeline. Expert evaluators ranked the results in the dimensions of credibility, validity, and interactivity. The agreement between the evaluators was moderate (Spearman $\rho = 0.71$), and we calculated a TrueSkill score [8] for each ablation, performed Kruskal-Wallis tests to determine the general differences between ablations, and applied Dunn's post hoc test [20] to isolate which specific condition differed from another.

3.2 Results

Segmentation Performance: Video transcript segmentation achieved 76.9% accuracy within the five-second threshold, providing acceptable performance for educational content. The accuracy decreased with longer videos, suggesting pre-segmentation into shorter clips (10-12 minutes) could improve results.

Table 2. Comparison of the intent performance across three video topics: exploratory data analysis (EDA), machine learning (ML), and game development (Game).

Topic	Knowledge			Method			Action			Interaction		
	Prec.	Recall	F1	Prec.	Recall	F1	Prec.	Recall	F1	Prec.	Recall	F1
Total	0.791	0.787	0.789	0.814	0.809	0.807	0.902	0.895	0.896	0.970	0.968	0.968
EDA	0.810	0.806	0.808	0.849	0.815	0.818	0.896	0.871	0.872	0.984	0.984	0.984
ML	0.795	0.798	0.796	0.825	0.809	0.807	0.900	0.899	0.899	0.956	0.944	0.947
Game	0.827	0.781	0.792	0.808	0.813	0.798	0.954	0.953	0.953	0.973	0.969	0.969

Controllability: As shown in Table 2, *CogGen* demonstrated strong alignment between intended and generated content across all dimensions. Knowledge extraction precision and recall were 0.791 and 0.787 respectively, indicating *CogGen* accurately generates messages according to specified knowledge without missing important content. Method alignment showed consistent performance across topics, with EDA videos performing slightly better. Action and Interaction components showed progressively stronger performance, demonstrating *CogGen*'s ability to reliably convert specified interactions into conversational utterances.

The ascending performance pattern (Knowledge → Method → Action → Interaction) reflects the natural refinement process as the system moves from general knowledge to specific interactions, leveraging work done in previous phases.

Component Importance: The full condition has the highest TrueSkill score ($\mu = 30.14, \sigma = 1.60$), suggesting that combining both knowledge induction and method planning is the most effective strategy. Knowledge-Only ($\mu = 26.11, \sigma = 1.40$) outperformed Method-Only ($\mu = 23.89, \sigma = 1.40$). This suggests that without knowledge induction, the method-only approach may fail to provide precise guidance tailored to the video content, potentially leading to over-scaffolding simple concepts or under-scaffolding more complex ones. In contrast, while the knowledge-only condition has a higher score than the method-only approach, it lacks the adaptive capability provided by method planning, making it less responsive to the student's mastery level. The baseline condition performed worst ($\mu = 19.86, \sigma = 1.60$).

Kruskal-Wallis test indicates significant differences between conditions ($p < 0.001; H = 32.86$), and Dunn's post-hoc test confirmed significant pairwise differences between all ablations ($p < 0.05$). These results demonstrate that each component in *CogGen* contributes significantly to generating effective and coherent guidance, and the full pipeline has the best results than other conditions.

4 Discussion and Conclusion

Our research demonstrates *CogGen*'s effectiveness in enhancing programming education through interactive video-based tutoring. The evaluation results confirm that *CogGen* successfully integrates learning science principles from the *CogApp* framework to generate targeted pedagogical interventions. The architecture's ability to segment videos by learning goals, maintain controllability across knowledge and pedagogical dimensions, and adapt instruction based on student performance addresses key challenges in LLM-based tutoring.

CogGen shows particular promise in formal classroom settings, where instructors can leverage its controllable parameters to create customized learning tasks within video-based lessons. The architecture's strengths lie in its structured prompting approach that maintains pedagogical coherence while allowing for personalized guidance. By integrating BKT-based student modeling with generative AI, *CogGen* represents a significant step toward scalable, adaptive programming education.

However, our current implementation has limitations that future work should address. While *CogGen* performs well with the three video topics in our evaluation, its effectiveness across more diverse programming tutorials requires further investigation. The architecture's current design assumes videos have a modular structure where segments align with discrete learning goals—an assumption that may not hold for tutorials with overlapping content. Future versions could implement adaptive segmentation using temporal coherence and multimodal cues to better align with instructional goals.

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