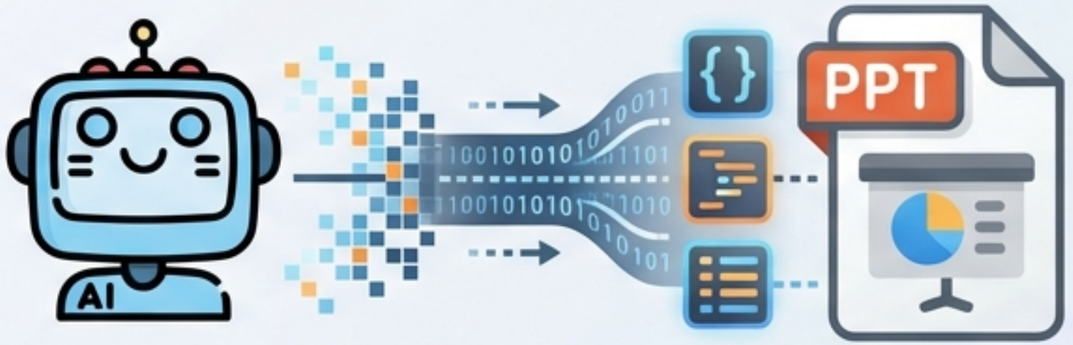
SlideCoder: Layout-Aware RAG-Enhanced Hierarchical Slide Generation

Converting Reference Images into Editable PowerPoint Scripts with Precision



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Context

The Challenge: Automated Slide Creation Fails at Fidelity

Current **Multimodal** LLMs (MLLMs) like AutoPresent attempt to automate slide creation from natural language. However, when tasked with replicating a visual **Reference Image (RI)**, they fail to capture the structural integrity of the design.

Visual Evidence

1. **Miss**: Complete omission of visual or textual elements.
2. **Incorrect**: Deviations in style (font weight, color, shape attributes).
3. **Disorder**: Significant errors in spatial arrangement and alignment.

Why MLLMs Struggle with Slide Generation

Visual Blindness

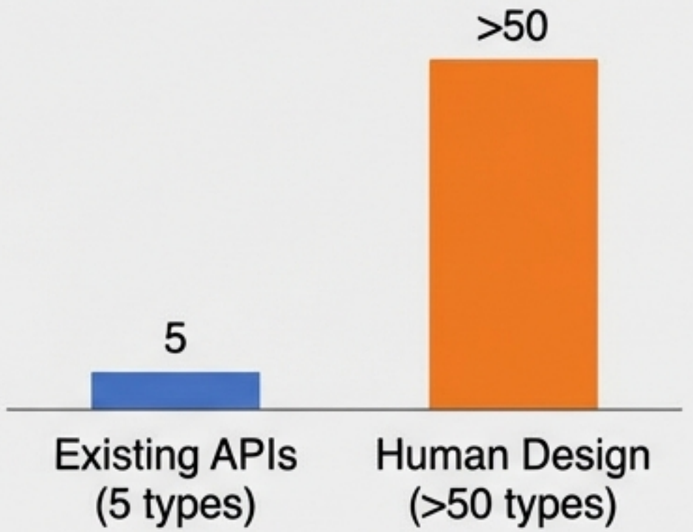
Natural language prompts cannot capture pixel-perfect layout nuances or the high density of elements in professional slides.

Library Ignorance

```
slide.shapes.add_magic_box()
```

General purpose MLLMs hallucinate python-pptx code, often using invalid syntax or non-existent APIs.

The Complexity Gap

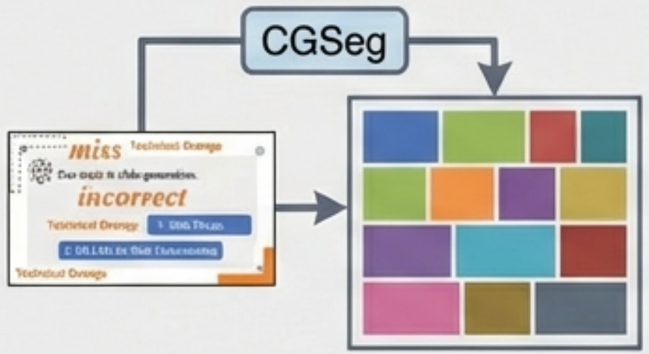


Current methods rely on simplified APIs (SLIDLILIB) that support only basic operations, failing to capture complex human design intentions.

Introducing SlideCoder: A Unified End-to-End Framework

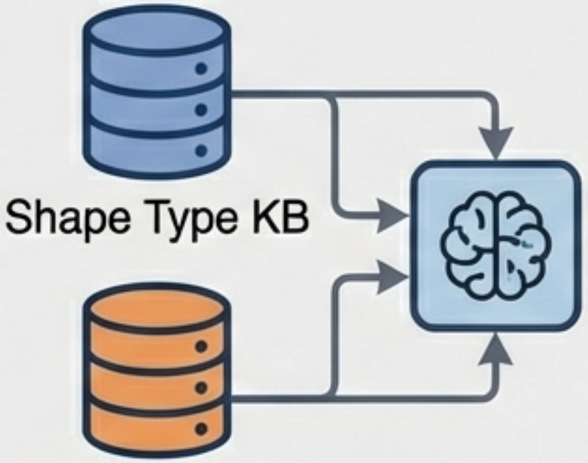
Divide and Conquer via Hierarchical Generation

Segmentation



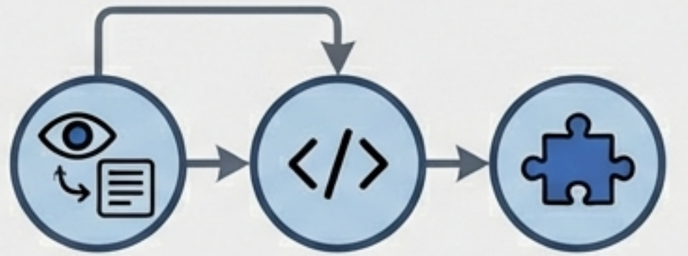
Decomposes slide images into semantically meaningful regions.

Hierarchical RAG



Injects specific knowledge to prevent code hallucinations.

Agent Workflow



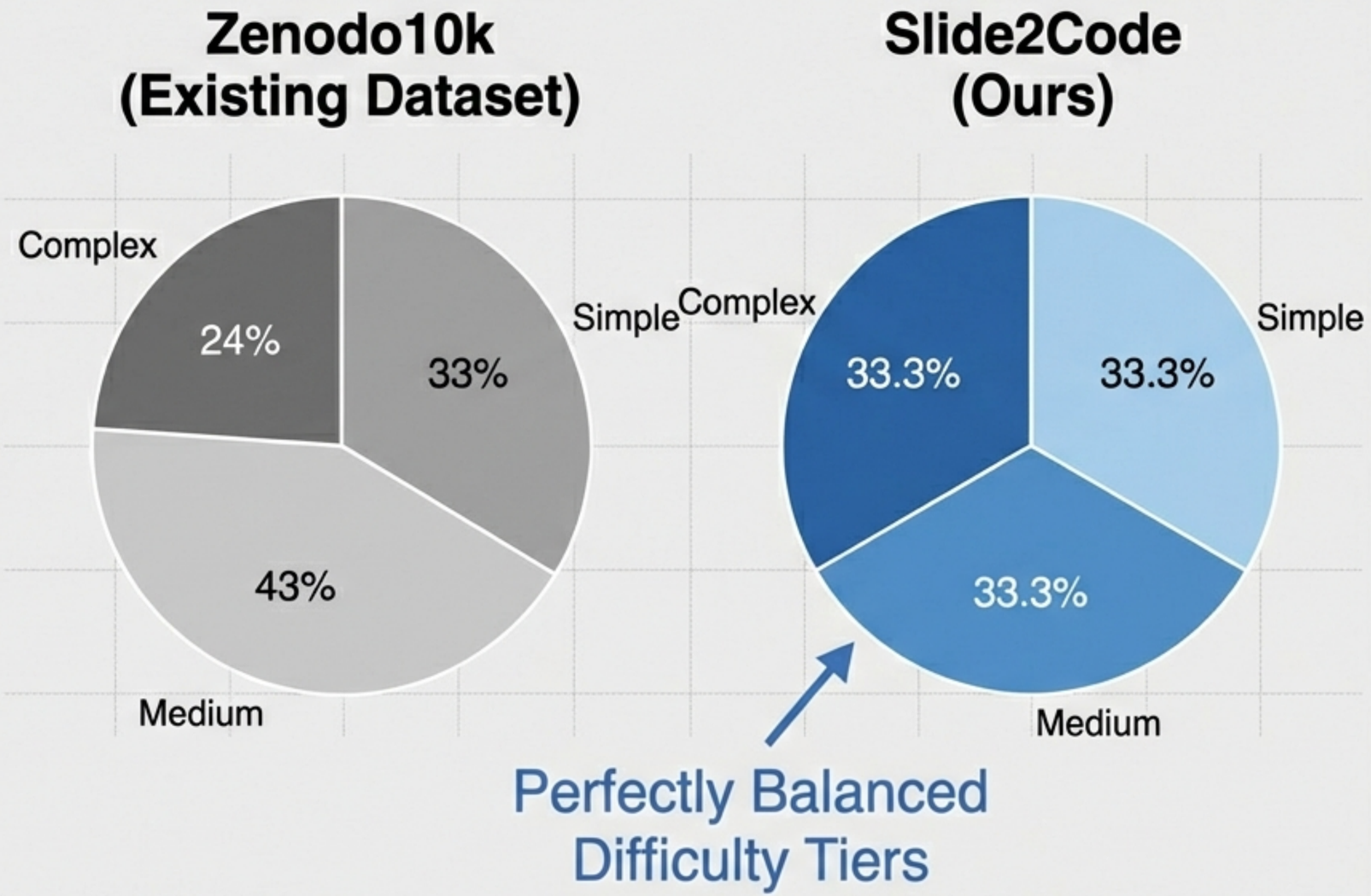
Multi-agent relay to generate and assemble final code.

Contribution 1: The Slide2Code Benchmark

New Task:
Reference Image (RI) to Slide Generation.

Goal: Generate Python code that replicates a provided image.

Data Source: Curated from ~32,000 candidates to select 300 high-quality samples.



Measuring Difficulty: The Slide Complexity Metric (SCM)

$$z_i = \alpha \cdot \tilde{c}_i + \beta \cdot \tilde{e}_i + \gamma \cdot \tilde{v}_i$$

Variable: c_i

Element Count

Total number of visual elements on the canvas.

Variable: e_i

Element Diversity

Count of distinct element types (textboxes, charts, shapes).

Variable: v_i

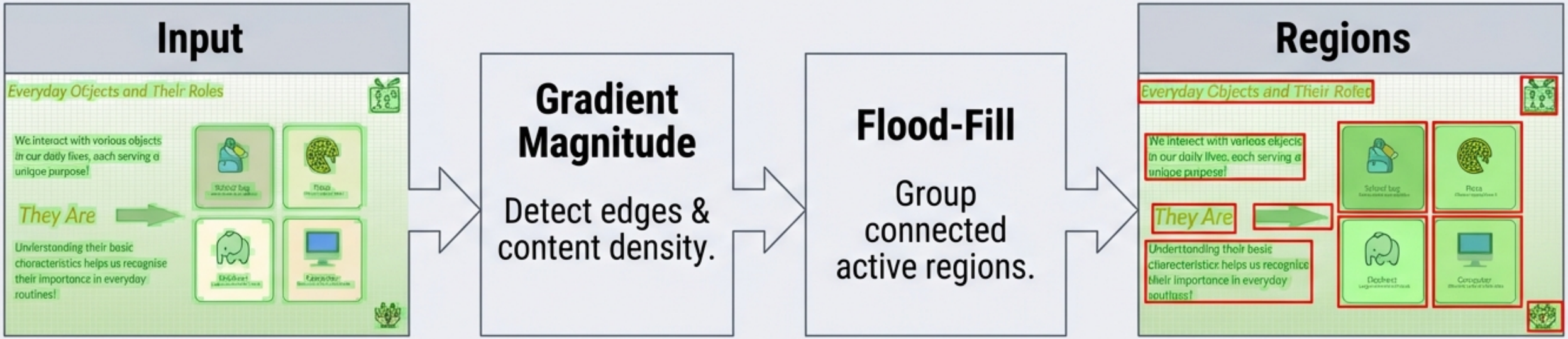
Visual Density

Element Coverage Ratio calculated via activated color grids.

Validation: SCM correlates strongly with human judgment ($r = 0.873$).

Methodology I: Color Gradient-based Segmentation (CGSeg)

Recursive decomposition based on visual density.



Methodology II: Hierarchical RAG (H-RAG)

Dual-layer knowledge injection for syntax correctness.

Concept

Level 1: Shape Type KB

Target Agent: Describer
Function: Standardizes terminology (e.g., 'Placeholder' vs 'Box').

```
{'Auto Shape': 'Predefined shape with approx 180 variations...'}
```

Level 2: Operation Function KB

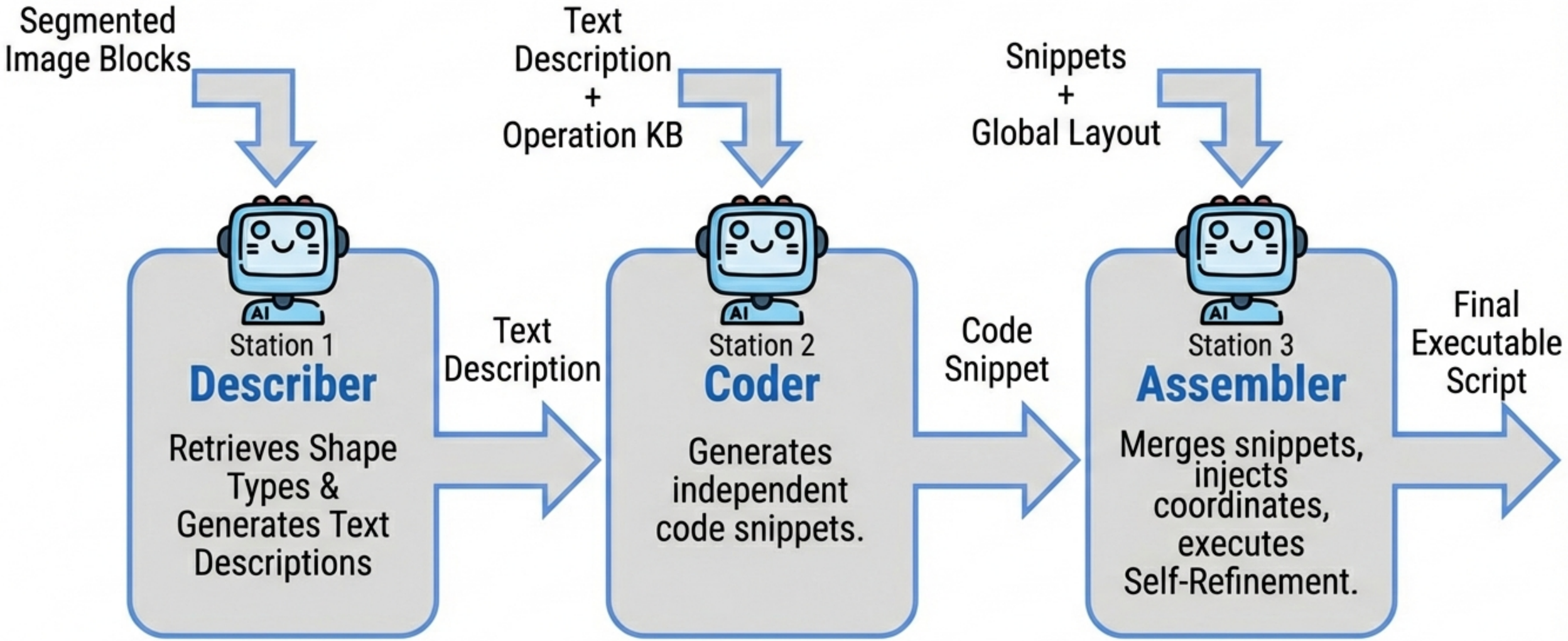
Target Agent: Coder
Function: Provides exact API syntax, parameters, and return values.

```
pptx.Presentation(pptx=None) -> Presentation object
```

Implementation

You are a python-pptx expert...
The following is an introducti to layout shape shape types in PPT:
{<Grammar>}

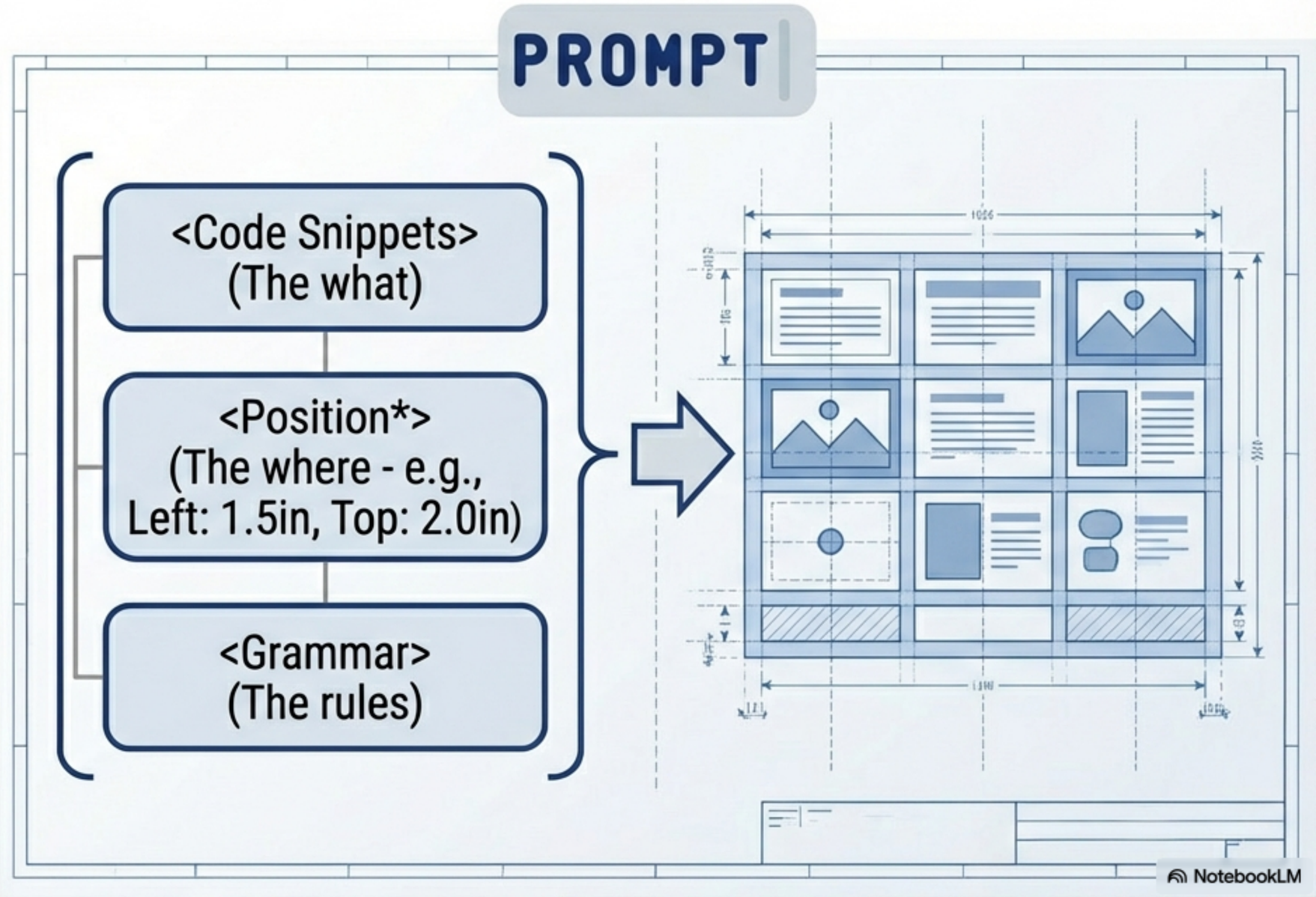
Methodology III: The Multi-Agent Workflow



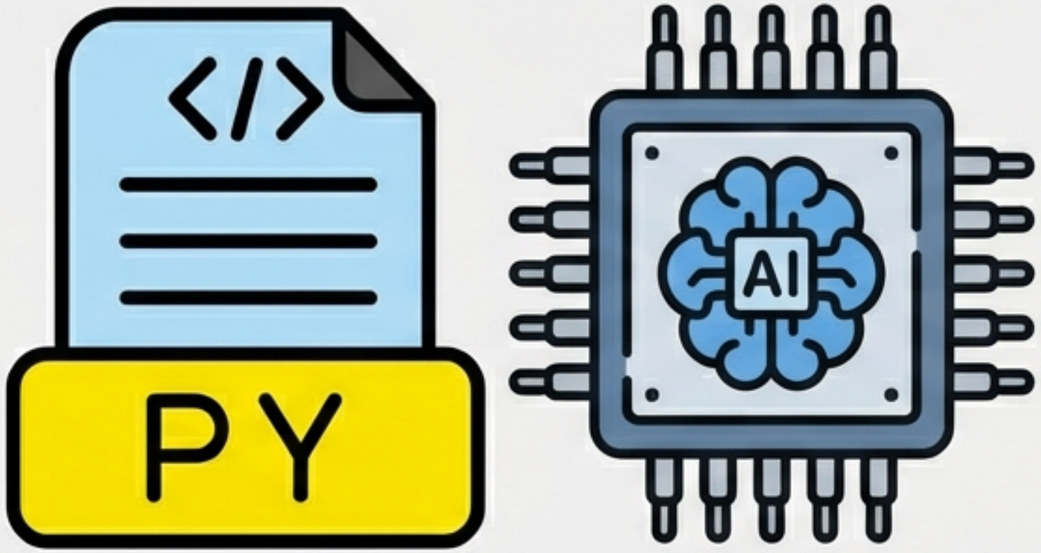
Methodology IV: Layout-Aware Prompting

The Challenge:
Local code snippets don't know where they belong on the global canvas.

The Fix:
Injecting relative coordinates (x, y, w, h) derived from CGSeg directly into the prompt.



SlideMaster: The Open-Source Contender



Base Model: Qwen2.5-VL-7B-Instruct

Training: Fine-tuned on high-quality (Image, Code) pairs.

The Secret Sauce: Custom PPTX Reverse-Engineering Tool

Feature	AutoPresent (Baseline)	SlideMaster (Ours)
Object Types	5	**10**
Styles	16	**44**
Complex Support	Basic Shapes	Tables, Connectors, Gradients

Quantitative Results: Dominating the Leaderboard

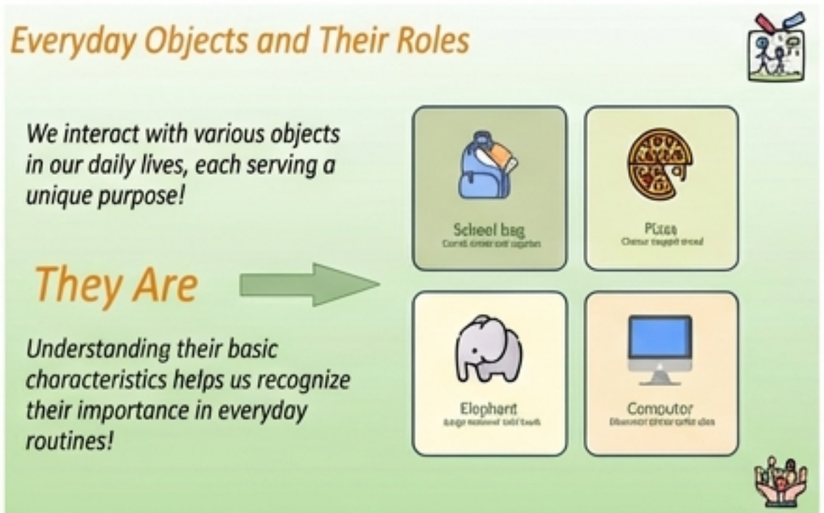
Framework	Difficulty	Execution Rate	Overall Score
AutoPresent (GPT-4o)	Simple	61.0%	80.3
Technical Green	Complex	41.4%	**53.0**
SlideCoder (GPT-4o)	Simple	**99.0%**	**91.8**
Technical Green	Complex	**85.5%**	**82.2**

On Complex tasks, SlideCoder outperforms the baseline by **40.5 points**.

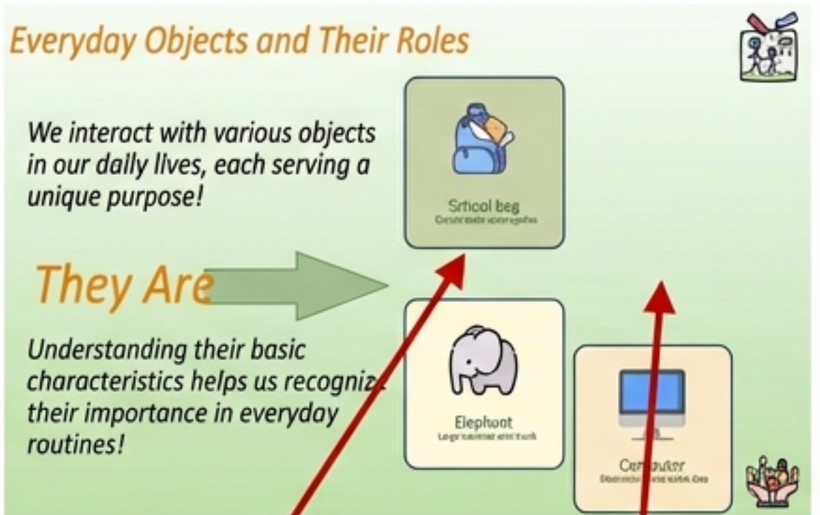
Execution Rate approaches **100%**, compared to ~40-60% for baselines.

Qualitative Comparison: Visual Fidelity

Reference Image (Input)



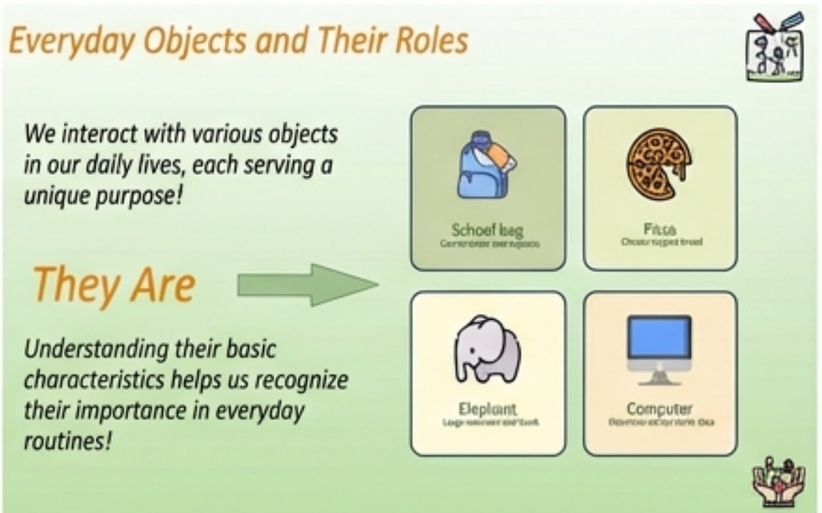
Baseline (AutoPresent)



Disorder

Miss

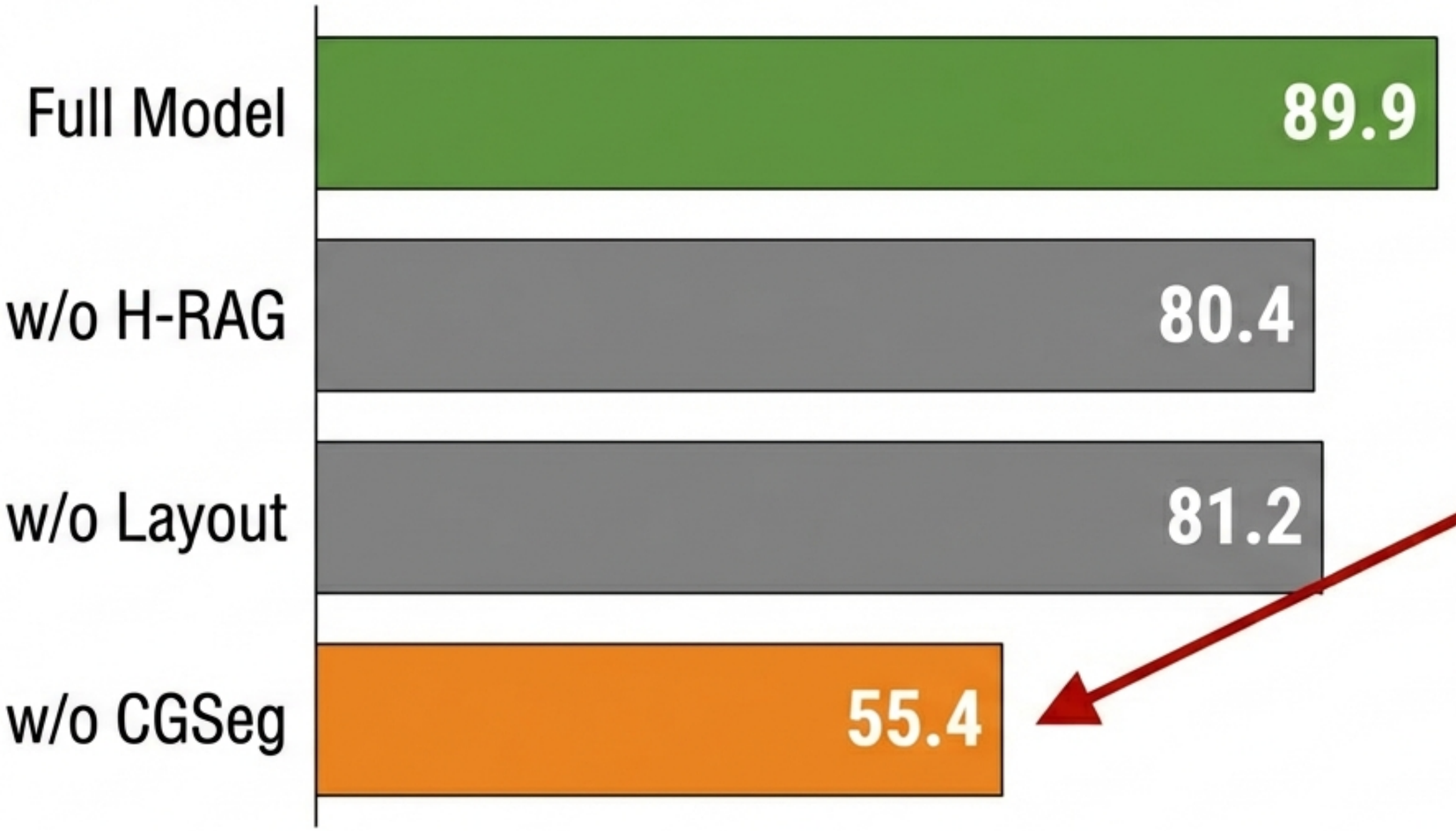
SlideCoder (Ours)



Preserves grid layout, icon placement, and text hierarchy.

Ablation Study: Why Every Component Matters

Impact of Removing Components (Overall Score on Simple Tasks)



Removing Segmentation (CGSeg) causes a massive performance drop. The model gets overwhelmed by the full slide image.

Conclusion & Future Directions

- **Slide2Code**: Established a rigorous new benchmark for complex slide generation.
- **SlideCoder**: Achieved SOTA by integrating Segmentation (CGSeg), Retrieval (H-RAG), and Layout-Aware Prompting.
- **SlideMaster**: Released an open-source 7B model that rivals proprietary giants like GPT-4o.

Future Work:

- Multi-slide generation capabilities.
- Handling full-slide background images without separate assets.

Code & Data Available: https://github.com/vinsontang1/SlideCoder