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Towards a Foundational Visual-Programmatic Interface for Code Intelligence

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JanusCoder: Towards a Foundational Visual-Programmatic Interface for Code Intelligence

Qiushi Sun*, Jingyang Gong*, Yang Liu*, Qiaosheng Chen*, Lei Li, Kai Chen, Qipeng Guo, Ben Kao, Fei Yuan



Background



The scope of **code intelligence** is rapidly expanding

beyond text-only coding tasks (e.g., LCB, SWE) to the rich **visual outputs** that programs generate (charts, UIs, animations), typically:

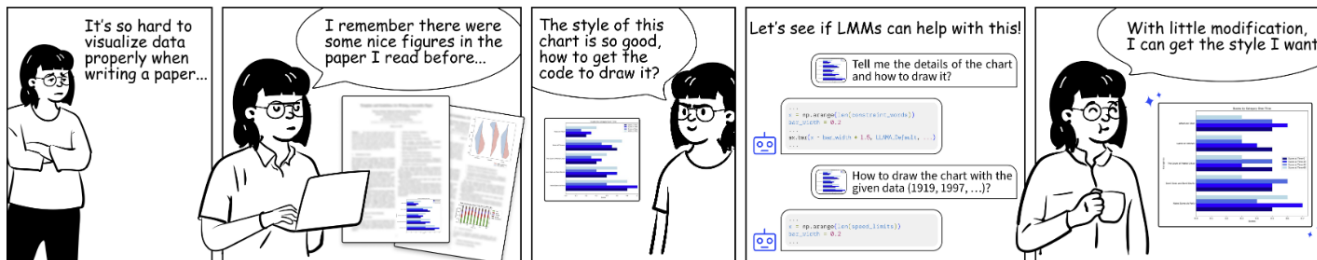
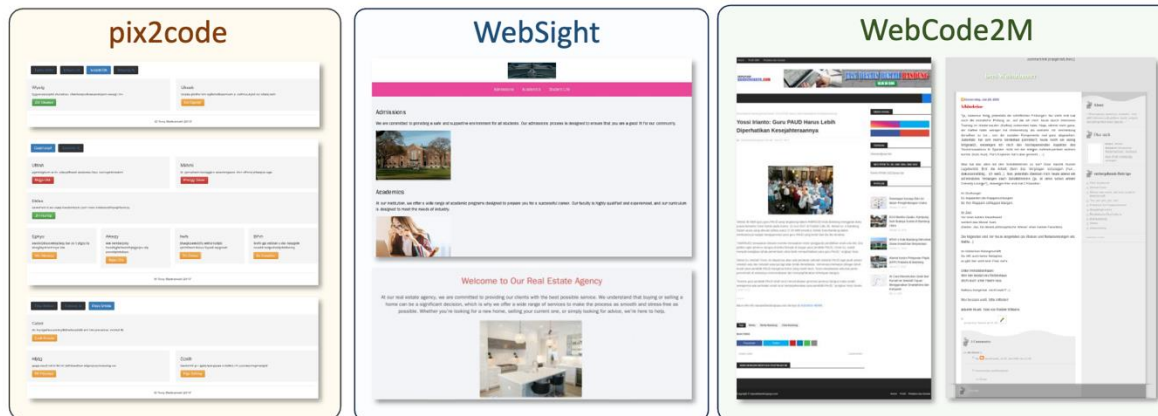


Chart2Code



Webpage to Code

Coding for **visual** contents!

Background



Coding for visual contents

Create a hierarchical sunburst (donut) chart to visualize the relationship between scientific software and their corresponding task categories, similar to the...

显示代码 <>

显示思路

scientific_e_sunburst

HTML

Python

```
import plotly.graph_objects as go
import numpy as np

# 1. Define the hierarchical data structure
# The root node will be implicit (") and we start with the applications.
# This structure creates the "hole" in the center.
Labels = [
    # Level 1: Applications
    'GrassGIS', 'Celestia', 'Kalegebra', 'ChimeraX', 'Lean4', 'TeXStudio',
    'Map Display', 'Image Analysis', 'Data Editing', 'Basic Manipulation',
    # Level 2: Task Types (Children of GrassGIS)
    'Simulation', 'Data Queries', 'Spatial Reasoning', 'Basic Settings',
    # Level 2: Task Types (Children of Celestia)
    'Basic Ops.', 'Direct Instructions', 'Open Problems', 'Adv. Knowledge',
    # Level 2: Task Types (Children of ChimeraX)
    'Software Config.', 'Struct. Analysis', 'Data Interp.', 'Struct. Prediction',
    # Level 2: Task Types (Children of Lean4)
    'Pure Math', 'Algebra', 'Geometry', 'Analysis',
    # Level 2: Task Types (Children of TeXStudio)
    'Basic Usage', 'Layout', 'Figure Editing'
]

parents = [
    # Level 1: Applications (All children of the implicit root "")
    "", "", "", "", "", "",
    # Level 2: Task Types (Children of GrassGIS)
    'GrassGIS', 'GrassGIS', 'GrassGIS', 'GrassGIS',
    # Level 2: Task Types (Children of Celestia)
    'Celestia', 'Celestia', 'Celestia', 'Celestia',
    # Level 2: Task Types (Children of Kalegebra)
    'Kalegebra', 'Kalegebra', 'Kalegebra', 'Kalegebra',
    # Level 2: Task Types (Children of ChimeraX)
    'ChimeraX', 'ChimeraX', 'ChimeraX', 'ChimeraX',
    # Level 2: Task Types (Children of Lean4)
    'Lean4', 'Lean4', 'Lean4', 'Lean4',
    # Level 2: Task Types (Children of TeXStudio)
    'TeXStudio', 'TeXStudio', 'TeXStudio', 'TeXStudio'
]
```



I found a very beautiful data visualization in the ScienceBoard paper, and I'd like to create a similar one. Please help me implement it using Python code.

显示思路

Certainly. That's an excellent visualization from the ScienceBoard paper, which benchmarks GUI agents on scientific software. This type of chart is a **nested pie chart**, also known as a **sunburst chart**.

You can create this in Python using **Matplotlib**. The main technique is to draw two separate pie charts on the same axes: one for the outer ring and one for the inner ring, setting their radii and widths carefully so they stack.

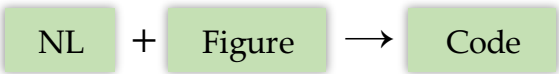
Here is the complete Python code to replicate the chart. I've extracted the data directly from the image you provided.

Python Code (using Matplotlib)

Python

```
import matplotlib.pyplot as plt
import numpy as np

# 1. Define the data structure from the image
# I've assumed sub-categories are equally weighted within their parent category.
```



Background



Coding for **visual and interactive** contents: WebUIs -> Generative UIs

To Do

Task 1

Urgent

This is the content for task 1.

Task 2

Low Priority

This is the content for task 2.

In Progress

Task 3

In Progress

This is the content for task 3.

Done

Task 4

Completed

This is the content for task 4.

Task Board

[Dashboard](#) [Projects](#) [Team](#) [Settings](#)

To Do5 pts

Task 13 pts

Urgent

This is the content for task 1.

Task 22 pts

Low Priority

This is the content for task 2.

In Progress8 pts

Task 38 pts

In Progress

This is the content for task 3.

Done5 pts

Task 45 pts

Completed

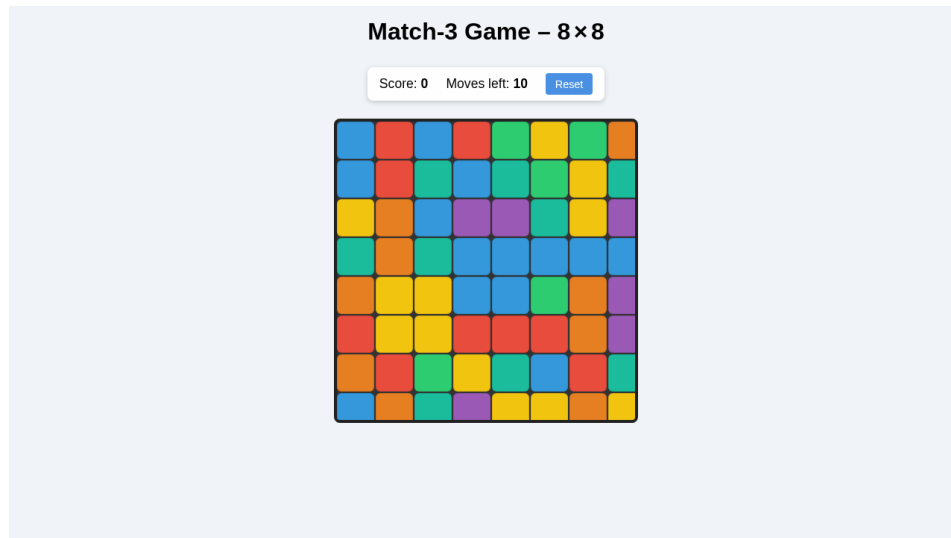
This is the content for task 4.

Given NL description + webpage screenshot, generate or edit the web UI.

Background



Coding for **visual and interactive** contents: artifacts / web demos

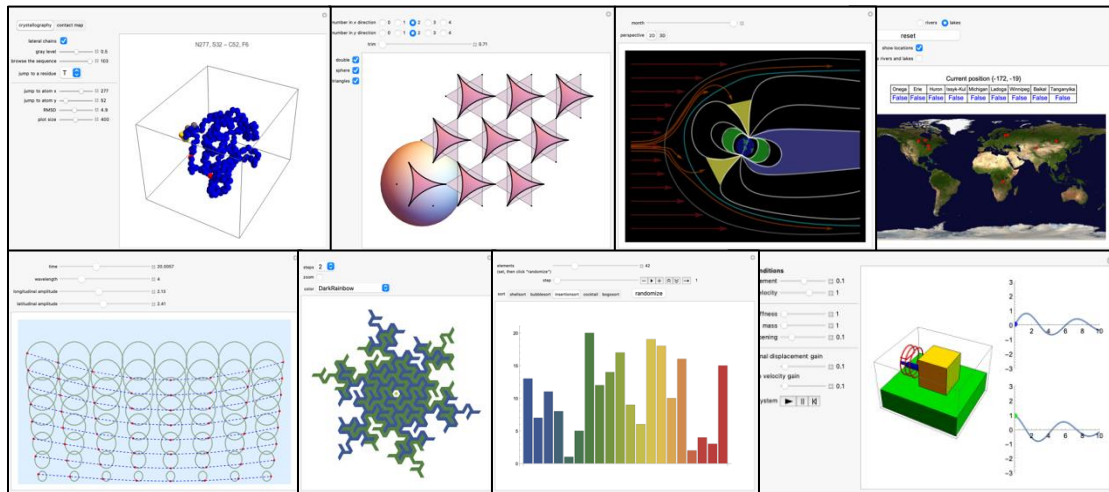


It is not only about visualization, but also about the **underlying logic, algorithms** ...

Background

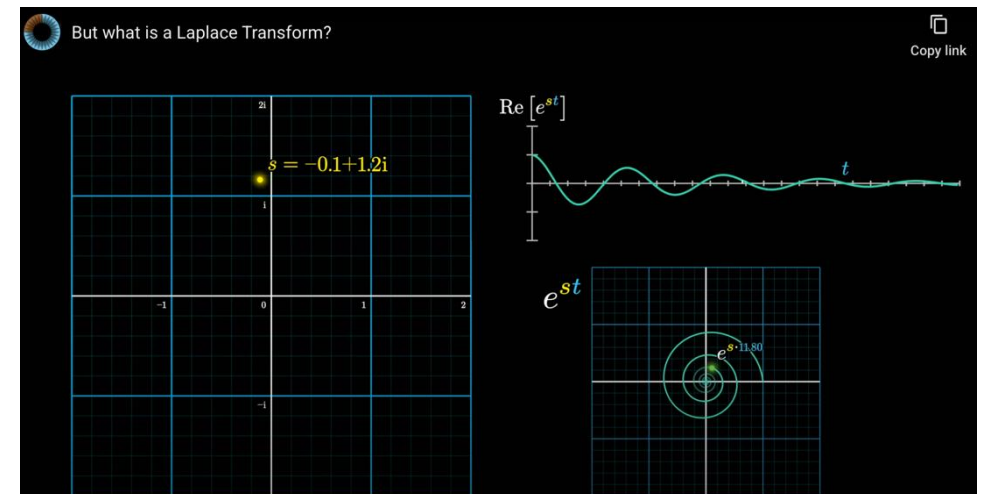


Coding for **visual and interactive** contents: scientific demos



“Code-driven demos”

3blue1brown video



“Code-driven videos”

Multimodal Code Intelligence



Leading players are also moving in this direction.

Qwen3-VL

3D Grounding	Generate accurate 3D bounding boxes for both model and dataset objects.	 Open in Colab
Thinking with Images	Utilize image_zoom_in_tool and search_tool to facilitate the model's precise comprehension of fine-grained visual details within images.	 Open in Colab
MultiModal Coding	Generate accurate code based on rigorous comprehension of multimodal information.	 Open in Colab
Long Document Understanding	Achieve rigorous semantic comprehension of ultra-long documents.	 Open in Colab
Spatial Understanding	See, understand and reason about the spatial information	 Open in Colab

Quickstart

Below, we provide simple examples to show how to use Qwen3-VL with  ModelScope and  Transformers.

Gemini 2.5 Pro

The Gemini 2.X series are all built to be natively multimodal, supporting long context inputs of >1 million tokens and have native tool use support. This allows them to comprehend vast datasets and handle complex problems from different information sources, including text, audio, images, video and even entire code repositories. These extensive capabilities can also be combined to build complex agentic systems, as happened in the case of Gemini Plays Pokémon¹ ([Zhang, 2025](#)). Different models in the series have different strengths and capabilities: (1) Gemini 2.5 Pro is our most intelligent thinking model, exhibiting strong reasoning and code capabilities. **It excels at producing interactive web applications, is capable of codebase-level understanding and also exhibits emergent multimodal coding abilities.** (2) Gemini 2.5 Flash is our hybrid reasoning model with a controllable thinking budget, and is useful for most complex tasks while also controlling the tradeoff between quality, cost, and latency. (3) Gemini 2.0 Flash is our fast and cost-efficient non-thinking model for everyday tasks and (4) Gemini 2.0 Flash-Lite is our fastest and most cost-efficient model, built for at-scale usage. A full comparison of the models in the Gemini 2.X model family is provided in [Table 1](#). Taken together,



However, it is clear that such capabilities come with a high barrier.

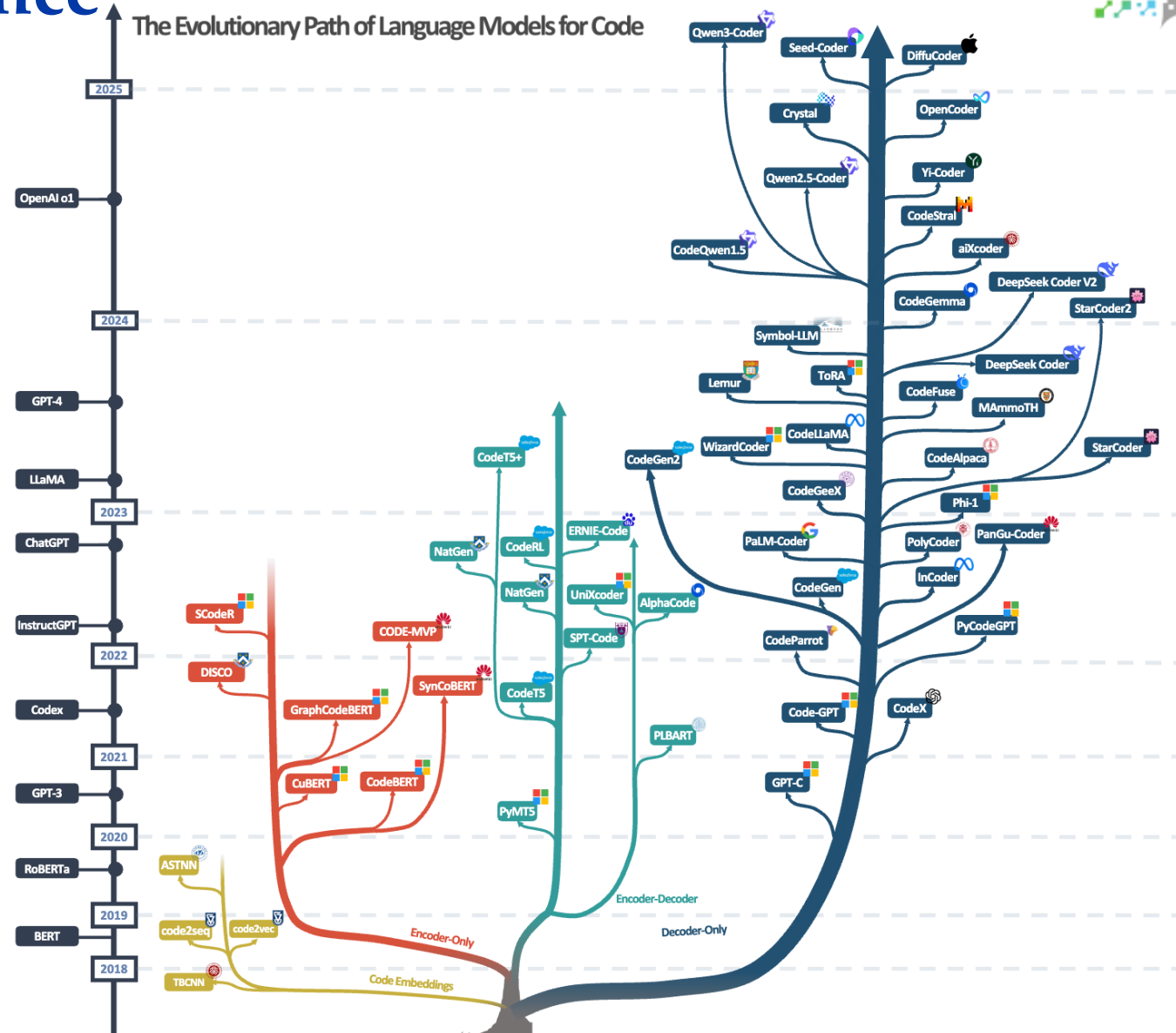
[1] <https://github.com/QwenLM/Qwen3-VL>

[2] Gemini 2.5: Pushing the Frontier with Advanced Reasoning, Multimodality, Long Context, and Next Generation Agentic Capabilities

Multimodal Code Intelligence

These capabilities are cool,
but they often require **specialized coding skills** and **multimodal** capability.

Challenge 1: Most current CodeLLMs are **text-based** and lack understanding of **visual content**.



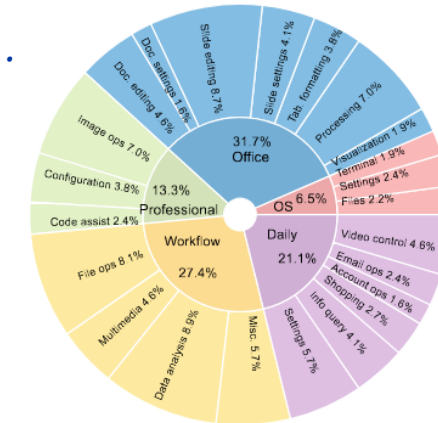
Multimodal Code Intelligence



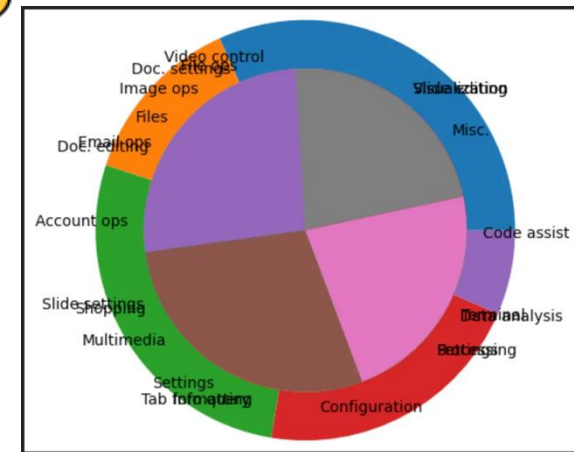
These capabilities are cool,
but they often require **specialized coding skills** and **multimodal** capability.

Challenge 2: General-purpose open-source VLMs perform poorly on **code + visual** tasks.

User: Please help me replicate....



User: 😞



Multimodal Code Intelligence



Challenge 3: Existing models, whether single or multimodal, are **task-specific** and **lack generalization ability**.

General models are fine-tuned to enable specific python visual, web-UI, or interactive content generation

This leads to the value and user experience differ greatly from proprietary ones.

Pure Text-based

VisCoder: Fine-Tuning LLMs for Executable Python Visualization Code Generation

Yuansheng Ni¹, Ping Nie⁴, Kai Zou³, Xiang Yue², Wenhui Chen¹,
¹University of Waterloo, ²Carnegie Mellon University, ³Netmind.ai, ⁴Independent Researcher,
{yuansheng.ni, wenhuchen}@uwaterloo.ca
<https://tiger-ai-lab.github.io/VisCoder>

Multimodal

ChartCoder: Advancing Multimodal Large Language Model for Chart-to-Code Generation

Xuanle Zhao^{1,*}, Xianzhen Luo^{2,*}, Qi Shi^{1,†}, Chi Chen^{1,†},
Shuo Wang¹, Zhiyuan Liu¹, Maosong Sun¹
¹ Tsinghua University, Beijing, China
² Harbin Institute of Technology, Harbin, China
2429527z@gmail.com, xzluo@ir.hit.edu.cn

VisCodex: Unified Multimodal Code Generation via Merging Vision and Coding Models

Lingjie Jiang^{1,2} Shaohan Huang^{1,†} Xun Wu¹ Yixia Li^{1,3} Dongdong Zhang¹ Furu Wei¹
¹ Microsoft Research ² Peking University ³ Southern University of Science and Technology
<https://aka.ms/GeneralAI>

Why Do We Need JanusCoder?



Landscape:

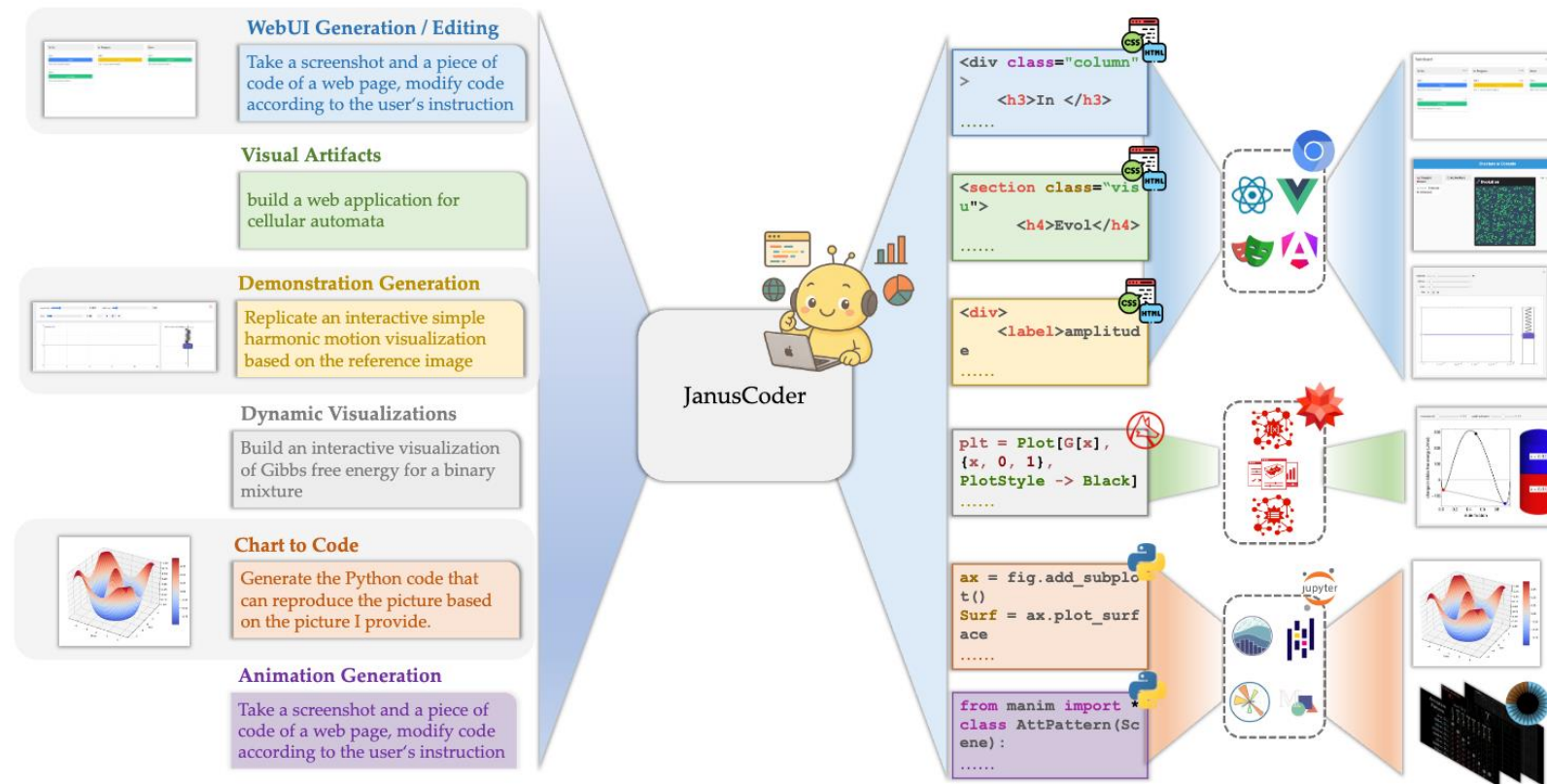
1. Research on such capabilities is still in its **early stage**, yet highly **valuable** (*e.g.*, for scientific demonstrations).
2. Proprietary models come with **high costs** and restricted research **accessibility**.
3. Existing works often built specialized models for **isolated** tasks (*e.g.*, one for charts, another for web UIs), resulting in limited generalization and poor scalability.

Therefore, we need a **unified, open-source Visual–Programmatic Interface** to **advance research in this domain**.

JanusCoder



We built **the first** suite of **unified** Visual-Programmatic Foundation Model.





The Core Problem: Progress in this domain has been blocked by the scarcity of high-quality, large-scale, and diverse data.

We need to cover multiple data types, but face several challenges:

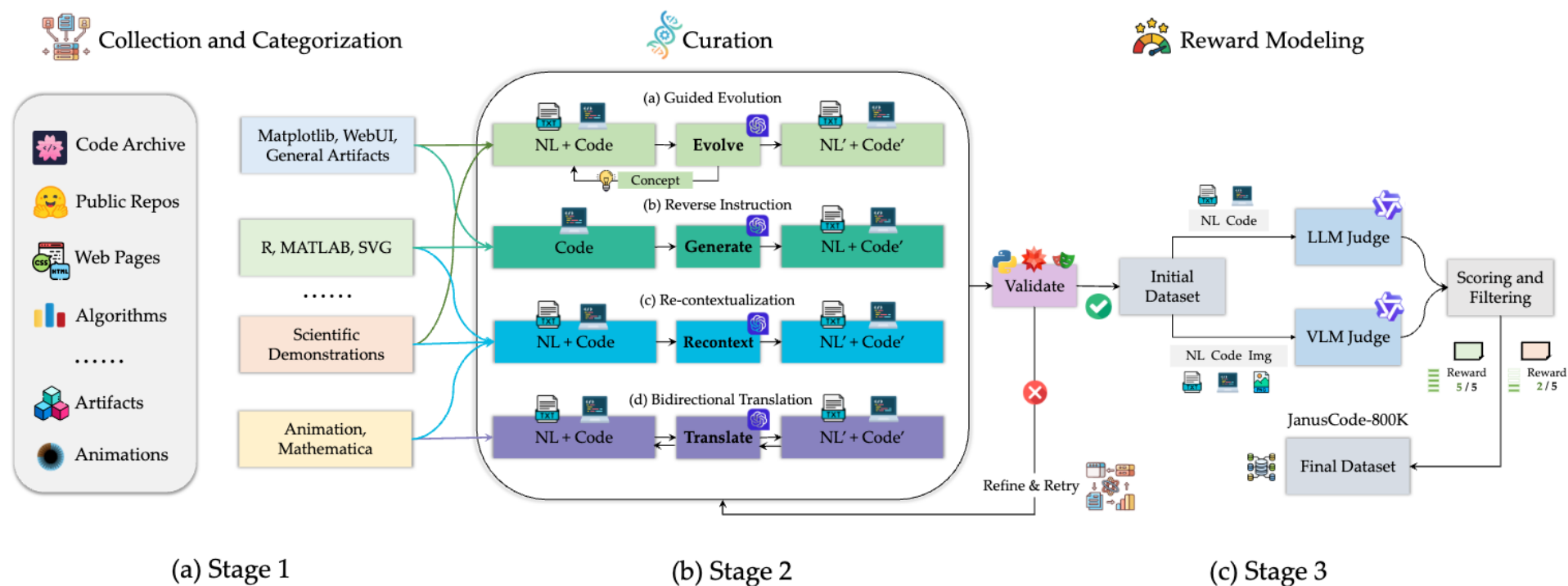
- (1) High-quality + Labeled data is **scarce**,
- (2) Category **imbalance** is severe, and
- (3) Demo and artifact data must be collected, cleaned, and constructed **from scratch**.

In this work, we try to solve the Data Bottleneck at its Source

JanusCoder



A comprehensive multimodal code data synthesis pipeline.



Rewarding: deterministic **signals** (compiler, renderer, etc.) + VLM/LLM-as-a-Judge evaluation.



For the same set of seed data, we **adopt diverse, adaptive strategies** to **synthesize data accordingly**.

Table 1: Overview of the strategies used to construct JanusCode Data from multiple sources, different colored squares represent different strategies: ■ Guided Evolution; ■ Re-contextualization; ■ Reverse Instruction; ■ Bidirectional Translation.

Source Data Type	Size	Validation	Reward	Strategies
Matplotlib	200K	Python	VLM	■ ■
Charts	77K	Python	VLM	■ ■
Algorithm	100K	Python	VLM	■
Mathematica	11K	Wolfram Engine	LLM	■ ■ ■
Animation	5K	Python + Manim Engine	VLM	■ ■
Scientific PLs	400K	-	LLM	■ ■ ■
SVG	400K	-	VLM	■
WebUI	270K	Playwright	VLM	■
General Artifacts	10K	Playwright	VLM	■ ■
Scientific demonstration	10K	Playwright	VLM	■

With the scale and diversity of data, we further explore the **synergistic** effects across different data types.

JanusCoder



The largest dataset to date for coding-driven visual content generation.

Table 2: Statistics of JANUSCODE-800K.

Data Type	Statistics
Text-centric	
Python Visualization: Generation	127.5K
Python Visualization: Editing	51.8K
Scientific PLs	31.8K
SVG	20.0K
Animation	19.5K
General Artifacts	56.8K
Algorithm Data	100.0K
Vision-centric	
Chart-to-Code	70.0K
WebUI Generation	200.0K
WebUI Editing	69.5K
Scientific demonstration	53.0K



Figure 3: Distribution of JANUSCODE-800K.



JanusCoder



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WebUI Generation	200.0K
WebUI Editing	69.5K
Scientific demonstration	53.0K



Figure 3: Distribution of JANUSCODE-800K.



It also includes **data types never seen in previous works.**

JanusCoder



It features (1) widest range of **tasks**, (2) largest data **scale**, and (3) broadest PL **coverage**.



Figure 3: Distribution of JANUSCODE-800K.



Competitors:

1. VisCode-200K: Python visualization only, single-modal (*Ni et al, 2025*)
2. MCD dataset: Traditional HTML, chart, QA tasks, 598K (*Jiang et al, 2025*)

This enables us to build a model that supports **all major single- and multimodal code-based visual content generation**.

JanusCoder



We present a suite of models to advance multimodal code intelligence.

JanusCoder-8B / 14B: based on Qwen3-8B / 14B 

JanusCoderV-7B / 8B: based on Qwen2.5-VL-7B  and InternVL3.5-8B 

We further validate the effectiveness of JanusCode-800K through experiments across backbones.

I plan to replace JanusCoderV's backbone with Qwen3-VL soon.



Let's start with the most typical case: Python visualization.

Table 3: Results on PandasPlotBench, ArtifactsBench, and DTVBENCH.

Model	PandasPlotBench			ArtifactsBench	DTVBENCH	
	Incorrect Code↓ (%)	Visual	Task		Manim	Wolfram
	Open-Source					
LLaMA3-8B-Instruct	26.9	59	69	36.5	4.92	3.15
Qwen3-8B	20.0	63	74	36.5	6.20	5.18
Qwen2.5-Coder-7B-Ins	21.1	63	76	26.0	8.56	4.04
Qwen3-14B	12.6	65	78	39.8	6.63	5.08
Qwen2.5-Coder-32B-Ins	12.0	66	82	35.5	9.61	4.98
JANUSCODER-8B	14.9	63	80	39.6	9.70	6.07
JANUSCODER-14B	9.7	67	86	41.1	8.41	5.97
	Proprietary					
GPT-4o	9.7	72	85	37.9	10.60	4.92

JanusCoder shows strong performance,

significantly outperforming open-source models of similar or larger size in code acc. and task completion

with some results matching or surpassing GPT-4o.



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Qwen2.5-Coder-32B-Ins	12.0	66	82	35.5	9.61	4.98
JANUSCODER-8B	14.9	63	80	39.6	9.70	6.07
JANUSCODER-14B	9.7	67	86	41.1	8.41	5.97
Proprietary						
GPT-4o	9.7	72	85	37.9	10.60	4.92



Strong results on the high-difficulty artifacts generation

Outperforming open-source baselines;

Application: Scientific visualization and demonstration

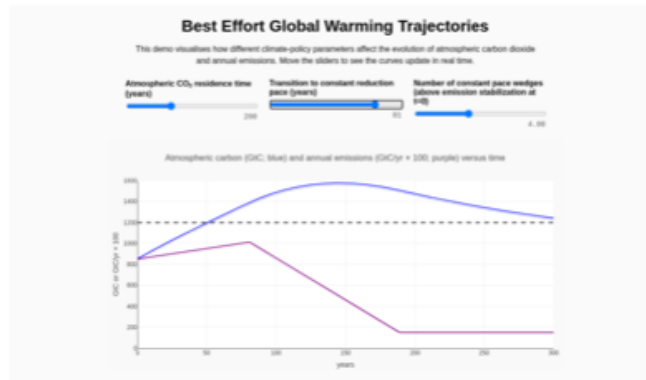
It can serve as a viable alternative to proprietary models,
Let's look at a few examples.

JanusCoder v.s. Gemini 2.5 Pro

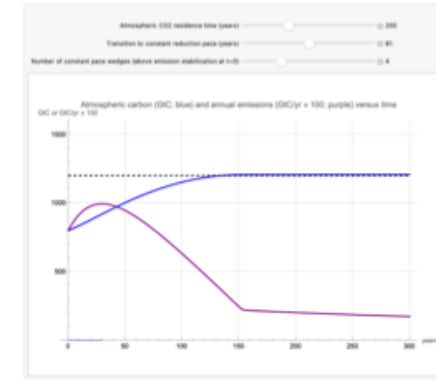
This demo visualises how different climate-policy parameters affect the evolution of atmospheric carbon dioxide and annual emissions. Move the sliders to see the curves update in real time.



Gemini-2.5-Pro

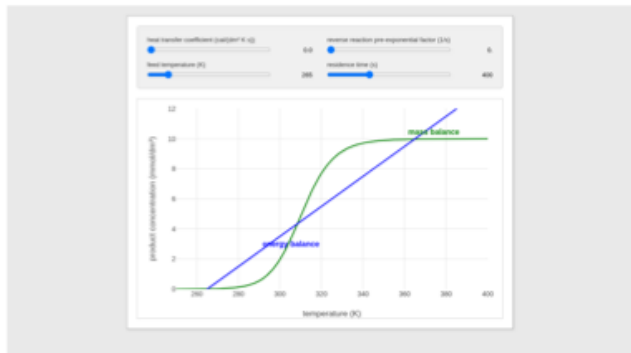


JanusCoder-8B

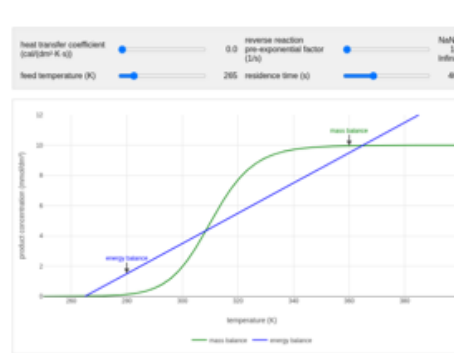


References

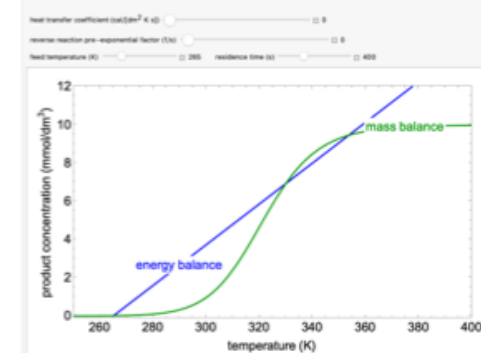
Multiple Steady States in a Continuously Stirred Tank Reactor



Gemini-2.5-Pro



JanusCoder-8B

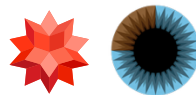


References



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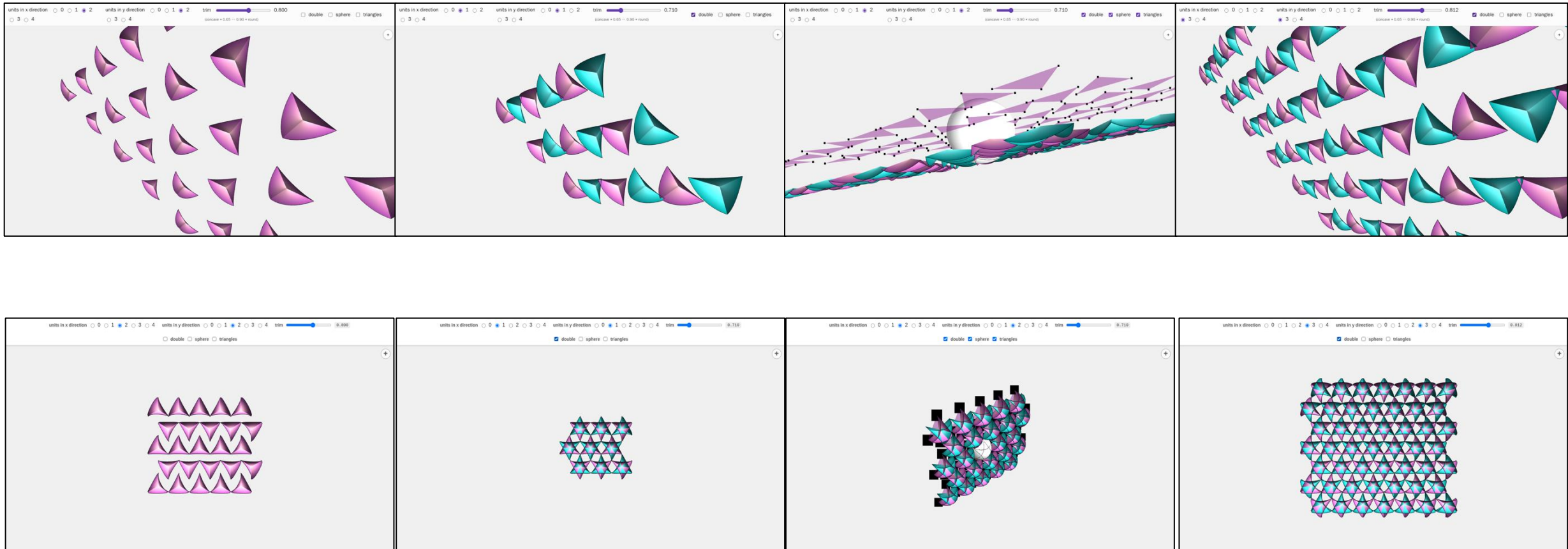
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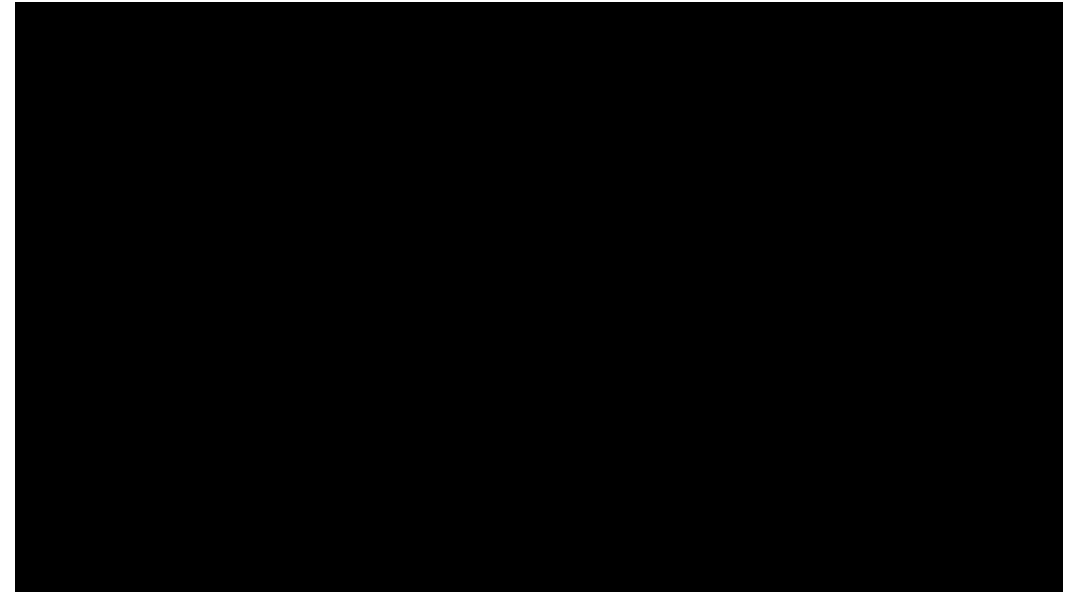
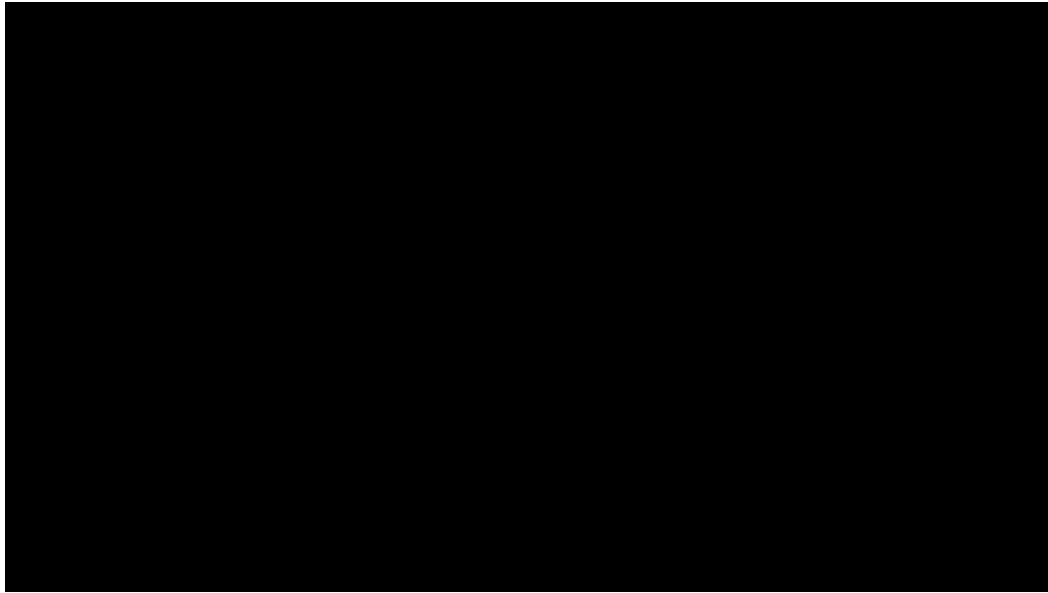


On the most challenging dynamic visualization tasks,
The performance is comparable to proprietary models.

Application: Creating 3Blue1Brown-style explanatory videos

JanusCoder





Helps create explanatory videos for scientific and educational subjects.



Table 4: Results on ChartMimic, DesignBench, WebCode2M, and InteractScience.

Model	ChartMimic				DesignBench		WebCode2M		InteractScience		
	Customized		Direct		Gen.	Edit.	Visual	TreeBLEU	Func.	Visual	
	Low	High	Low	High					Overall	CLIP	VLM
	Open-Source										
Qwen2.5-VL-7B-Ins	51.07	58.69	40.73	41.70	72.73	6.85	73.42	12.83	8.40%	45.86	19.83
InternVL3-8B	51.88	60.04	48.48	55.41	69.34	7.76	79.62	12.40	8.93%	53.35	22.05
InternVL3.5-8B	51.56	59.55	46.02	53.39	71.73	8.63	79.09	11.95	11.47%	56.79	24.17
MiniCPM-V-2-6	27.53	48.18	21.82	45.26	66.25	4.56	45.85	9.73	0.13%	20.65	7.70
Llama-3.2-11B-Vision-Ins	18.87	39.63	19.32	28.37	62.24	6.61	51.54	6.57	6.67%	32.87	13.24
JANUSCODERV-7B	64.72	72.77	65.73	72.73	73.31	8.79	75.78	26.21	17.73%	60.56	27.67
JANUSCODERV-8B	66.68	74.20	65.79	73.18	68.86	8.63	66.34	18.28	17.60%	61.52	33.32
	Proprietary										
GPT-4o	59.4	67.42	57.16	64.62	76.83	9.23	82.67	13.00	27.20%	70.14	46.01

JanusCoderV largely outperforms proprietary models on the chart-to-code task.



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JANUSCODERV-7B	64.72	72.77	65.73	72.73	73.31	8.79	75.78	26.21	17.73%	60.56	27.67
JANUSCODERV-8B	66.68	74.20	65.79	73.18	68.86	8.63	66.34	18.28	17.60%	61.52	33.32
Proprietary											
GPT-4o	59.4	67.42	57.16	64.62	76.83	9.23	82.67	13.00	27.20%	70.14	46.01

On web UI tasks, it performs strongly in both in-domain and out-of-domain settings.

The web UI generation and editing capabilities are closely related to its strength in scientific demonstrations.



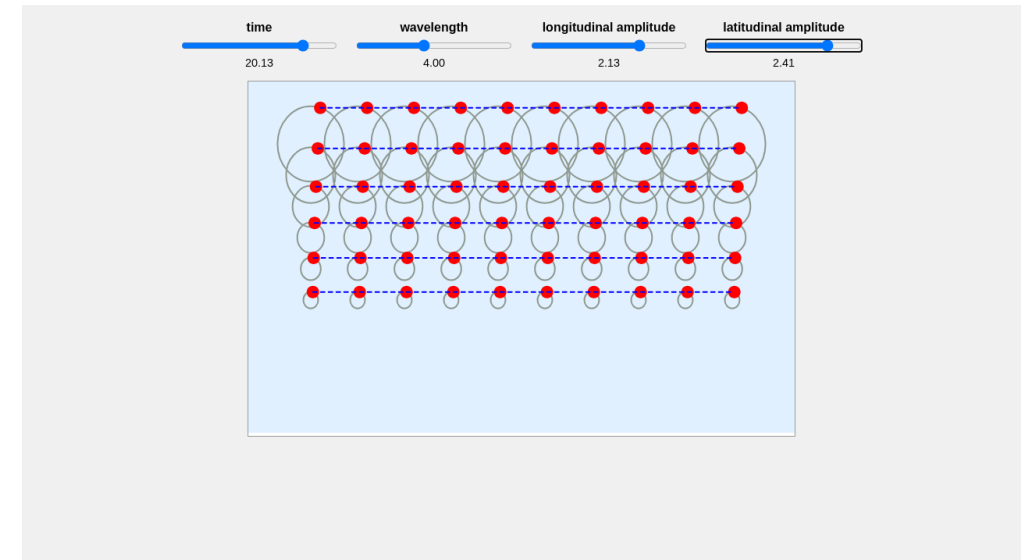
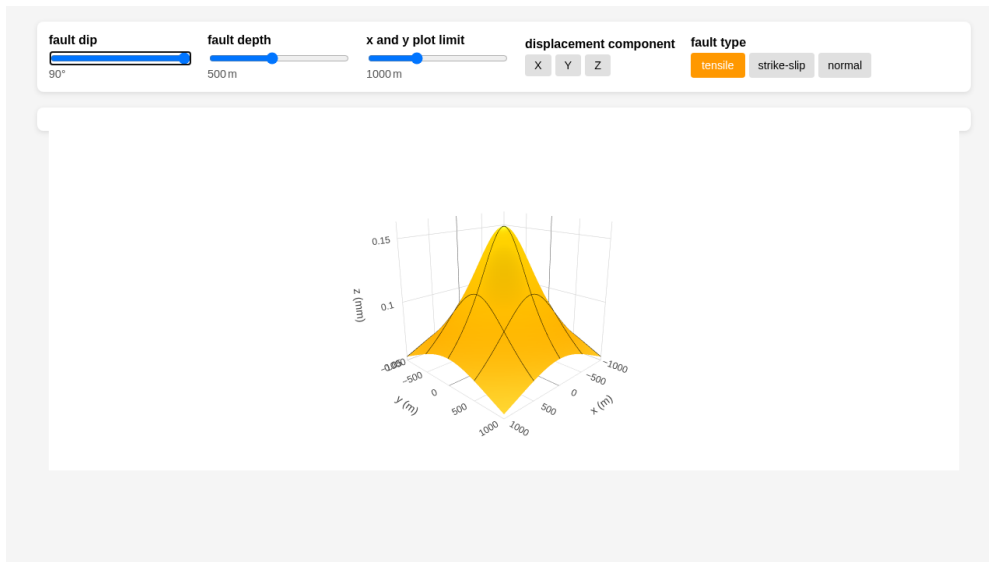
Table 4: Results on ChartMimic, DesignBench, WebCode2M, and InteractScience.

Model	ChartMimic				DesignBench		WebCode2M		InteractScience		
	Customized		Direct		Gen.	Edit.	Visual	TreeBLEU	Func.	Visual	
	Low	High	Low	High					Overall	CLIP	VLM
Open-Source											
Qwen2.5-VL-7B-Ins	51.07	58.69	40.73	41.70	72.73	6.85	73.42	12.83	8.40%	45.86	19.83
InternVL3-8B	51.88	60.04	48.48	55.41	69.34	7.76	79.62	12.40	8.93%	53.35	22.05
InternVL3.5-8B	51.56	59.55	46.02	53.39	71.73	8.63	79.09	11.95	11.47%	56.79	24.17
MiniCPM-V-2-6	27.53	48.18	21.82	45.26	66.25	4.56	45.85	9.73	0.13%	20.65	7.70
Llama-3.2-11B-Vision-Ins	18.87	39.63	19.32	28.37	62.24	6.61	51.54	6.57	6.67%	32.87	13.24
JANUSCODERV-7B	64.72	72.77	65.73	72.73	73.31	8.79	75.78	26.21	17.73%	60.56	27.67
JANUSCODERV-8B	66.68	74.20	65.79	73.18	68.86	8.63	66.34	18.28	17.60%	61.52	33.32
Proprietary											
GPT-4o	59.4	67.42	57.16	64.62	76.83	9.23	82.67	13.00	27.20%	70.14	46.01

Exhibits strong multimodal scientific demo generation, achieving performance close to proprietary models.

Can extend the application scope of scientific multimodal foundation models.

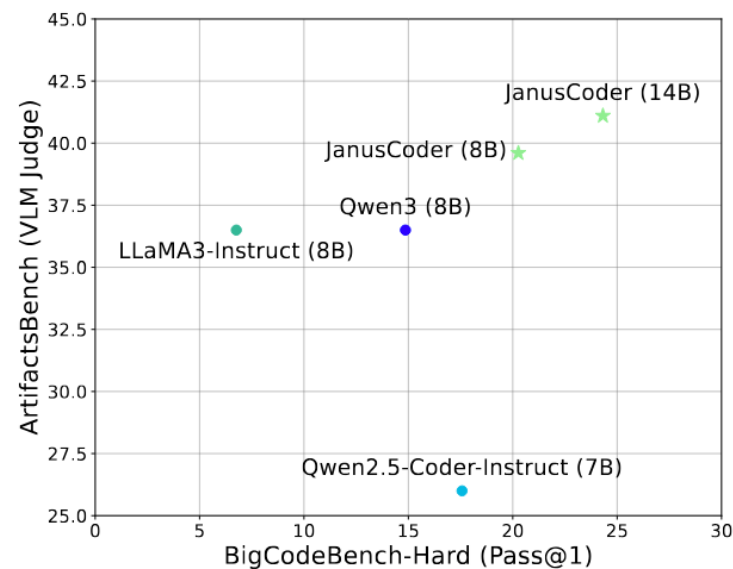
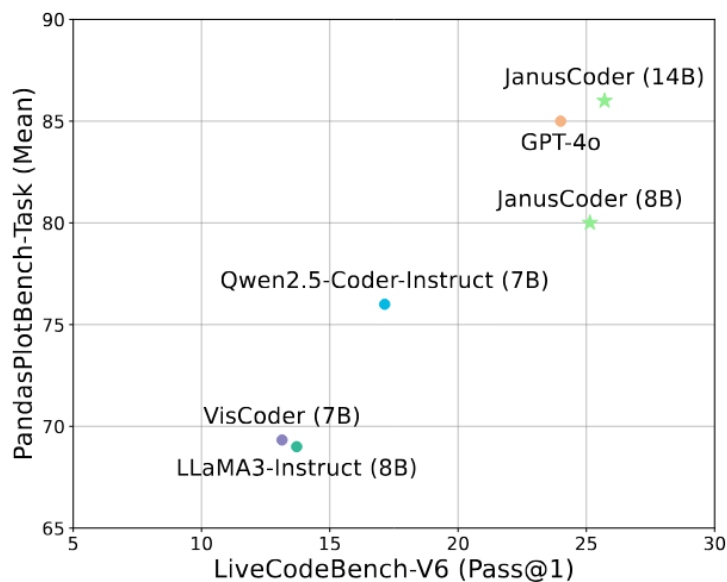
Given a sketch, it can generate interactive scientific demonstrations.



JanusCoder



While achieving strong visual content generation, JanusCoder also retains **good general coding capability**.



Potential: Multimodal Programming + Visualization Assistant

JanusCoder

Our unified data generalize well :)

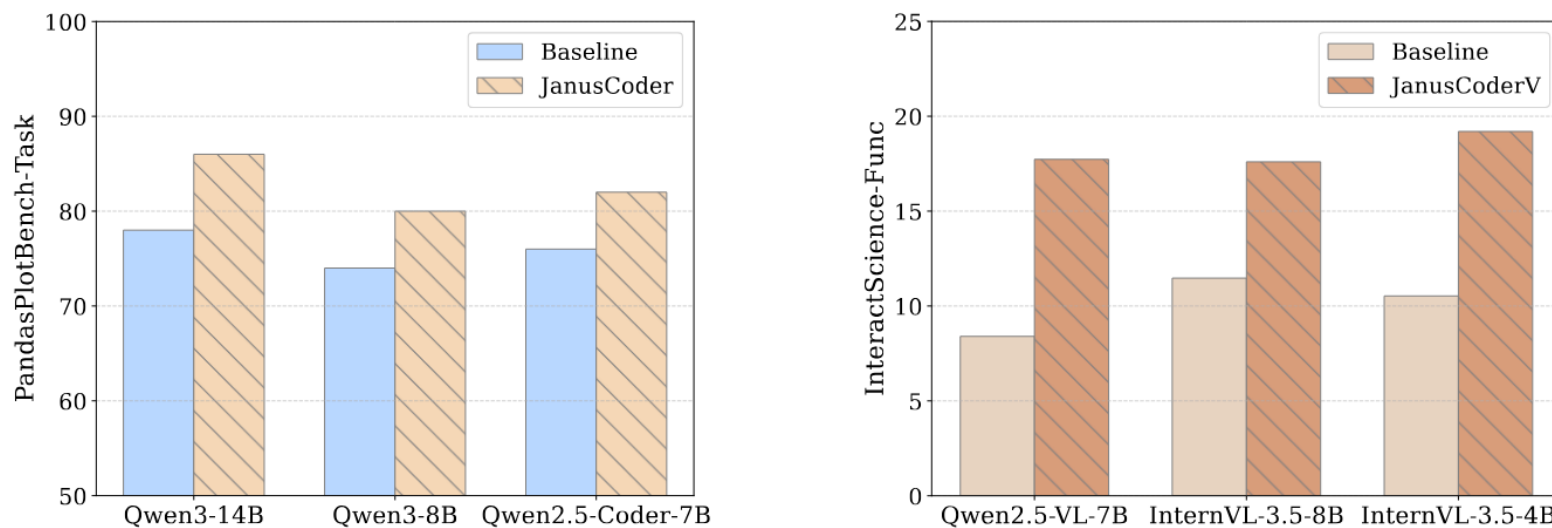


Figure 4: Effectiveness on different model backbones

Performs strongly across **different backbones**, suggesting the **data synthesis pipeline is generalizable and reusable**.



Thanks for listening

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