SPREADSHEETBENCH

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- 1 Ideas
- 2 Details
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- **6** Motivation

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Five Key Ideas

- Collect high-quality data from real-world sources and select the questions by rigorous criteria
- Utilize GPT-4 to recreate a coherent instruction
- Categorize answer positions into sheet-level and cell-level
- Create multiple spreadsheets and develop multiple test cases for each instruction
- Use various methods to mitigate data leakage



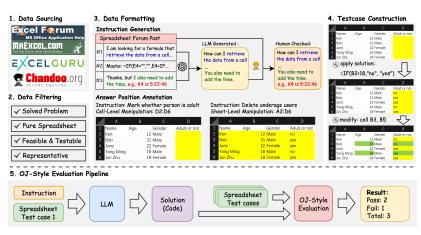


Figure 1: The benchmark construction pipeline and OJ-style evaluation.

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Data Info

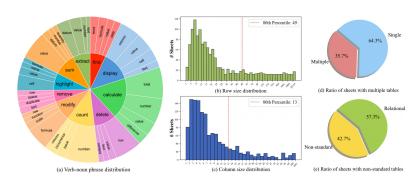


Figure 2: Key statistics of SPREADSHEETBENCH.

Data Leakage

Issue: Datasets initially **obtained from online** forums may be susceptible to data leakage issues, given that many LLMs are pre-trained using a vast corpus of web text.

Solutions:

- Revise the original questions in the posts during the Instruction Generation process.
- modifying the original provided spreadsheets during the Spreadsheet Modification.
- alter the position of the tabular data in the original spreadsheets and the corresponding answer in the resulting spreadsheets during the Answer Position Changing



Soft Restriction:

Details

$$S_{\text{soft}} = \frac{1}{|D|} \sum_{i=1}^{|D|} \left(\frac{1}{|T_i|} \sum_{j=1}^{|T_i|} 1_{r_i = ACC} \right)$$

Hard Restriction:

$$S_{hard} = \frac{1}{|D|} \sum_{i=1}^{|D|} 1_{rij} = ACC, \forall j = 1, 2, \dots, |T_i|$$

SPREADSHEETBENCH

Inference Setting

Evaluate LLMs under two distinct settings:

- Single-Round: present the model with the initial few rows of spreadsheet files within the prompt, allowing for **only one** inference.
- Multi-Round: Building on the single-round prompt setting, furnish error feedback if the code fails to execute, enabling the model to refine its code in subsequent iterations.

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LLM Processing

 $https://github.com/RUCKBReasoning/SpreadsheetBench \\ https://github.com/gersteinlab/MedAgents$

- Select datasets.
- 2 Pass function parameters.
- 3 Based on the function parameters, choose:
 - Dataset
 - Model type
 - Processing method
 - Output location
- Extract, clean, and format the data, then pass it to the large model.
- **6** Utilize the large model and the established pipeline for processing.
- 6 Output the processed results to files or other locations.
- 7 Use the evaluation module to assess and score the results.



- Prompt Engineering: Designing precise prompts to guide LLMs towards generating higher-quality responses by framing the input effectively.
- Fine-Tuning: Adapting an LLM to specific domains by training it on domain-specific datasets, improving its performance in that area.
- Chain-of-Thought (CoT): Encouraging step-by-step reasoning in the model, simulating how humans break down complex tasks into simpler steps to enhance logical consistency.
- **Self-Consistency (SC)**: Generating multiple independent reasoning chains for the same problem and choosing the most frequent answer to reduce randomness and errors.



Enhancing LLM Problem-Solving

- Multi-Round Interaction: Enabling the model to refine its answers through multiple rounds of interaction, adjusting based on user feedback for improved accuracy.
- Multi-Agent System: Introducing multiple agents or models to collaboratively solve tasks, leveraging diverse skills and knowledge for more effective problem-solving.
- Retrieval-Augmented Generation (RAG): Combining generation with information retrieval, allowing the model to fetch relevant information from external knowledge sources to improve answer accuracy.
- Classical Algorithms: For example, using C4.5 Discretization for data handling and PCA for data analysis and preprocessing.



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Table 2: Performance of representative models on SPREADSHEETBENCH (%).

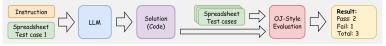
Model	Soft Restriction (↑)			Hard Restriction (↑)		
	Cell-Level	Sheet-Level	Overall	Cell-Level	Sheet-Level	Overall
Binder (GPT-3.5)	1.58	0.05	1.17	0.00	0.00	0.00
CodeQwen (7B)	0.36	0.76	0.51	0.36	0.29	0.33
w / Multi-Round	1.49	7.14	3.66	0.89	6.29	2.97
DeepseekCoder (33B)	0.59	5.81	2.60	0.36	5.14	2.20
w / Multi-Round	3.15	8.76	5.31	1.96	6.86	3.85
Mixtral-8x7B	2.97	3.33	3.11	2.32	2.57	2.42
w / Multi-Round	3.39	4.67	3.88	2.32	3.71	2.85
Llama-3 (70B)	0.18	3.14	1.32	0.00	2.86	1.10
w / Multi-Round	1.13	7.90	3.74	0.71	7.14	3.18
GPT-3.5	1.31	3.99	2.34	0.71	3.13	1.64
w / Multi-Round	3.33	13.11	7.09	2.50	9.97	5.37
GPT-40	15.03	23.65	18.35	11.94	19.94	15.02
w / Multi-Round	13.49	22.51	16.96	10.52	17.66	13.27
SheetCopilot (GPT-4)*	16.67	10.00	14.00	=	<u>-</u>	-
Copilot in Excel*	23.33	15.00	20.00	-	-	
Human Performance	75.56	65.00	71.33	66.67	55.00	62.00

Figure 3: Performance of representative models on SPREADSHEETBENCH %.



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- The concept of constructing a benchmark:
 - Data quality
 - Data construction
 - Data diversity
- Methods to address data leakage issues
- Developing a pipeline for evaluating problems using LLMs



 Some methods to enable LLMs to handle problems more effectively



Thanks!