

# Empowering and Assessing the Utility of Large Language Models in Crop Science





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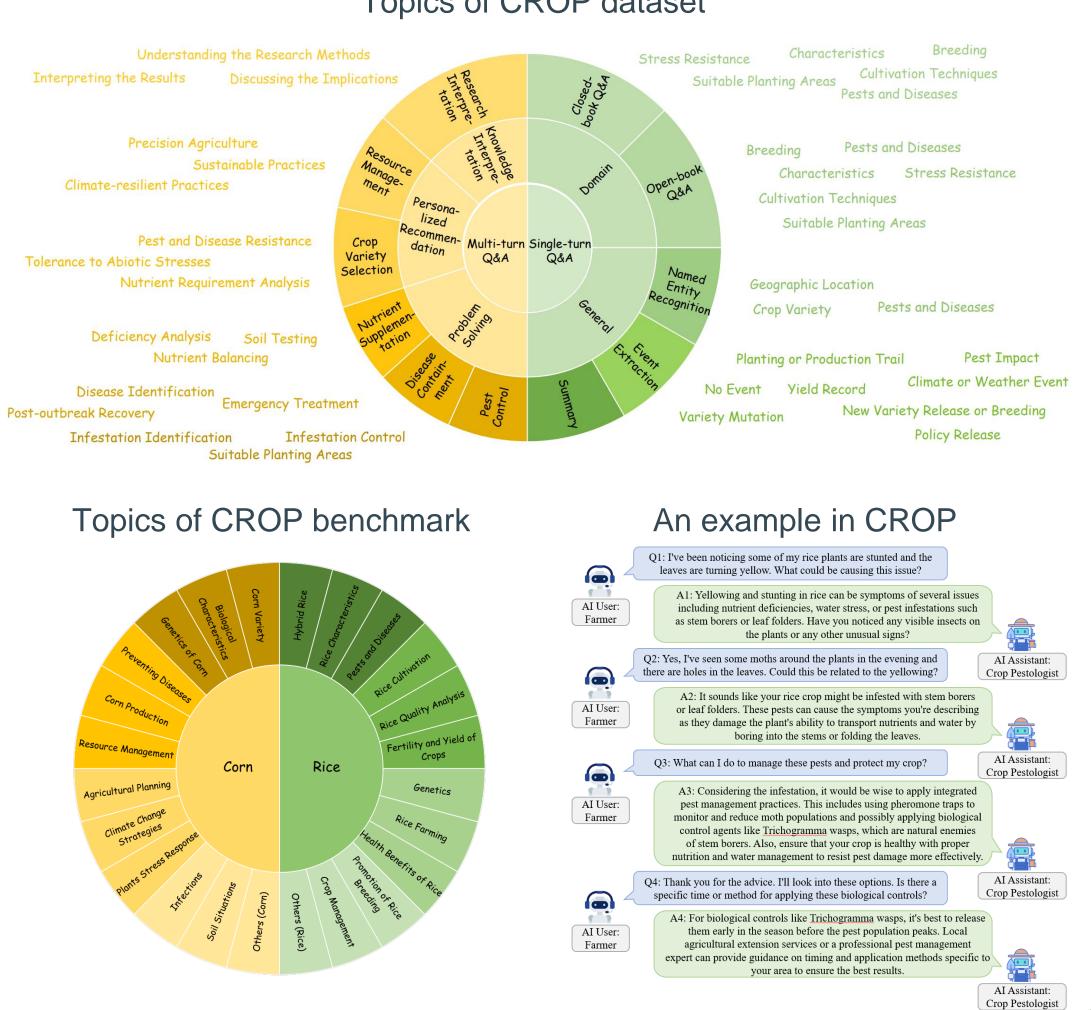
## 1. Motivation for the CROP

- Crop cultivation has historically been a significant challenge, with uncertainties in harvest yields.
- Recent progress in large language models (LLMs), offers promising opportunities. LLMs can generate professional knowledge and context in response to user inquiries, finding applications in various fields.
- However, LLMs currently face limitations in specific areas, such as pest management, and the existing datasets for agricultural evaluation are insufficient in quantity and locality.

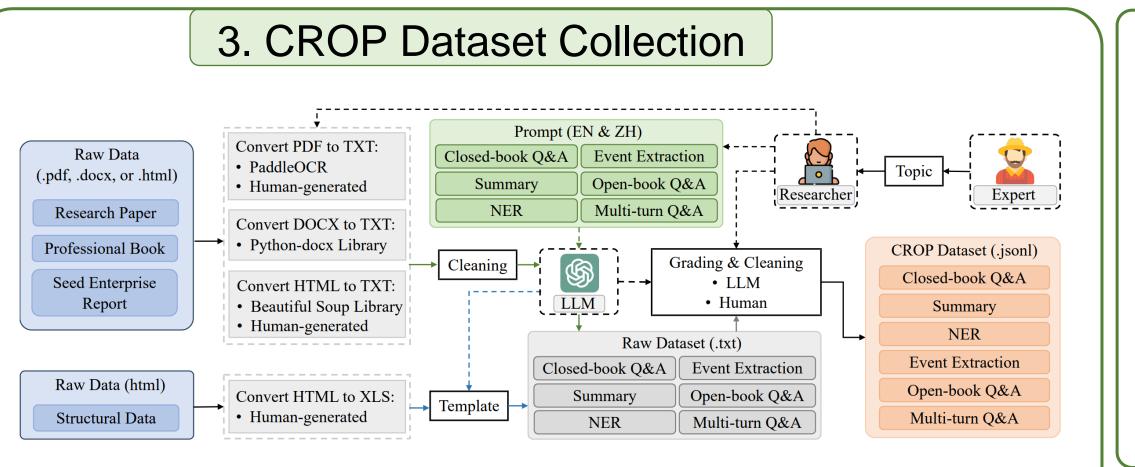
# 2. Overview of the CROP

To harness the full potential of LLMs for crop science, we propose a suite called CROP, which encompasses

- an extensive instruction-tuning dataset, designed to enhance the domain-specific proficiency of LLMs in crop science.
- a meticulously constructed benchmark, aimed at assessing the performance of LLMs across a variety of domain-related tasks.

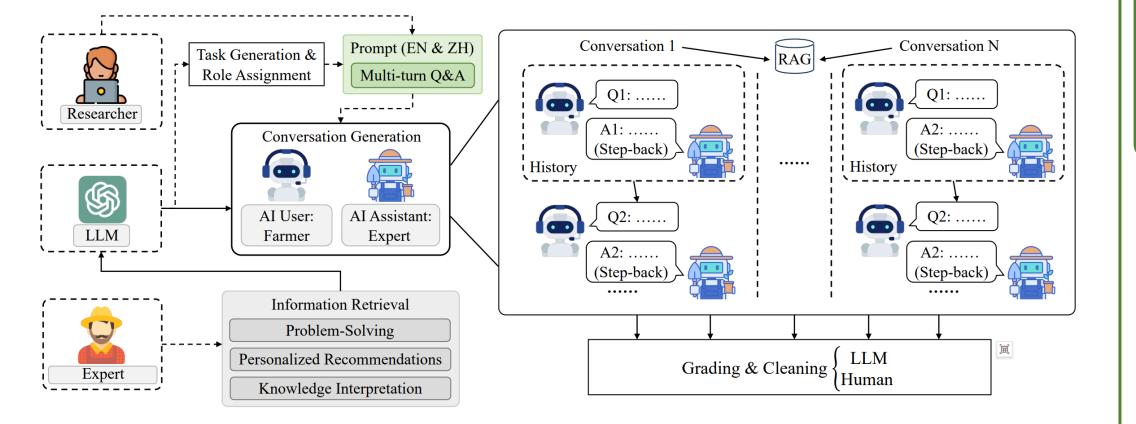


### **Topics of CROP dataset**



Single-turn dialogue collection pipeline:

- Raw data is first converted to TXT or XLS format.
- Prompt an LLM to generate Q&As from unstructured data or design templates that transform structured data into dialogue format.
- Filtering steps with both human and LLM involved.

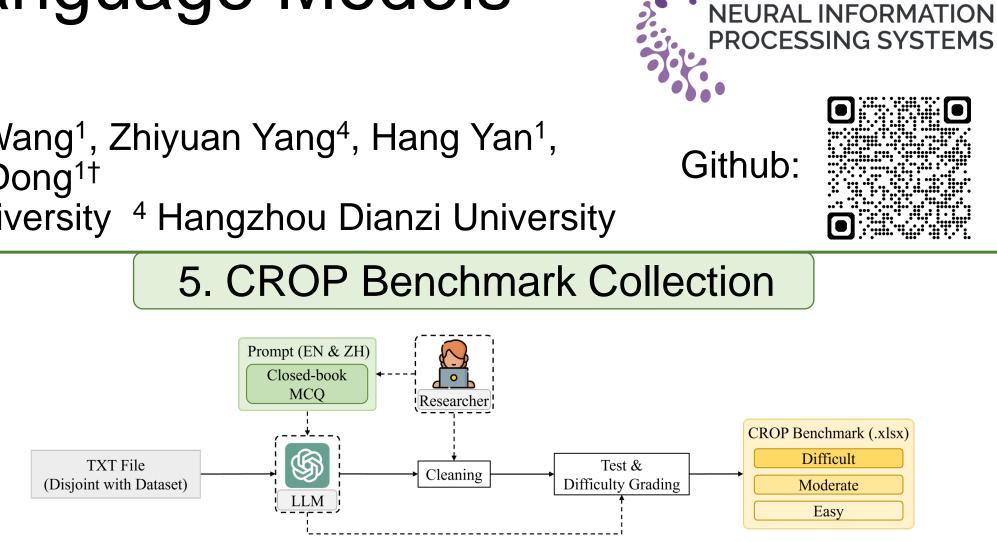


Multi-turn dialogue collection pipeline:

- An LLM creates tasks under the guidance of domain experts and assigns roles to two agents.
- Using task-dependent prompts from researchers, the LLM generates dialogues with RAG.
- Filtering steps.

# 4. CROP Dataset Analysis

- The single-turn dialogues comprise 210,038 high-quality samples.
- > 140,056 dialogue samples for rice
- ➢ 69,482 dialogue samples for corn
- The multi-turn dialogues include 1,871 high-quality samples.
- > Each task within the multi-turn dialogues has at least 80 samples
- > 3-5 turns of dialogue



• We prompt an LLM to generate MCQs from TXT files.

• After additional filtering steps with both human and LLM involved, we get the CROP benchmark, comprising three difficulty levels.

# 6. CROP Benchmark Analysis

• 5,045 questions in the benchmark have three difficulty levels:

➤ Easy (1613, 31.97%)

➢ Moderate (2754, 53.72%)

➢ Difficult (722, 14.31%)

 CROP benchmark consists of 5045 Chinese and English MCQs and covers 22 countries across six continents.

# 7. Experiments

• The performance of selected LLMs on the CROP benchmark

Model	Access	Size	Overall ↑	Difficulty							
				Easy ↑	Moderate $\uparrow$	Difficult ↑					
Commercial LLMs											
GPT-4 <sup>1</sup>	API	N/A	0.856	$1.000^{2}$	$1.000^{2}$	$0.000^{2}$					
GPT-3.5 <sup>1</sup>	API	N/A	0.328	$1.000^{2}$	$0.000^{2}$	0.061					
Claude-3 <sup>1</sup>	API	N/A	0.900	0.982	0.968	0.458					
Qwen <sup>1</sup>	API	N/A	0.866	0.987	0.945	0.301					
Open-source LLMs											
LLaMA3-Base	Weights	8B	0.348	0.443	0.341	0.161					
+CQIA	Weights	8B	0.643 (+0.295)	0.791 (+0.348)	0.651 (+0.310)	0.281 (+0.120)					
+CROP	Weights	8B	0.752 (+0.404)	0.866 (+0.432)	0.772 (+0.431	0.378 (+0.217)					
+CQIA+CROP	Weights	8B	0.754 (+0.406)	0.918 (+0.475)	0.779 (+0.438)	0.295 (+0.134)					
Qwen1.5-Base	Weights	7B	0.646	0.799	0.646	0.302					
+CQIA	Weights	<b>7B</b>	0.688 (+0.042)	0.880 (+0.081)	0.689 (+0.043)	0.258 (-0.044)					
+CROP	Weights	7B	0.676 (+0.030)	0.849 (+0.050)	0.688 (+0.042)	0.202 (-0.100)					
+CQIA+CROP	Weights	7B	0.709 (+0.063)	0.910 (+0.111)	0.704 (+0.058)	0.227 (-0.075)					
InternLM2-Base	Weights	7B	0.368	0.445	0.381	0.148					
+CQIA	Weights	7B	0.723 (+0.355)	0.861 (+0.416)	0.750 (+0.369)	0.317 (+0.169)					
+CROP	Weights	<b>7</b> B	0.748 (+0.380)	0.945 (+0.500)	0.761 (+0.380)	0.212 (+0.064)					
+CQIA+CROP	Weights	7B	0.768 (+0.400)	0.939 (+0.494)	0.794 (+0.413)	0.285 (+0.137)					

#### • The performance of LLMs under various training epochs and languages.

Model	Epoch	Size	Overall ↑	Difficulty			Language		
		5120		Easy ↑	Moderate ↑	Difficult ↑	Chinese ↑	English $\uparrow$	Variation $\downarrow$
LLaMA3-Base	N/A	8B	0.348	0.443	0.341	0.161	0.327	0.369	4.2%
+CQIA+CROP	1	8B	0.738	0.903	0.758	0.292	0.719	0.757	3.8%
+CQIA+CROP	2	8B	0.742	0.902	0.772	0.271	0.729	0.755	2.6%
+CQIA+CROP	4	8B	0.754	0.918	0.779	0.295	0.738	0.770	3.2%
Qwen1.5-Base	N/A	7B	0.646	0.799	0.646	0.302	0.667	0.624	4.3%
+CQIA+CROP	1	7B	0.702	0.910	0.717	0.183	0.725	0.680	4.5%
+CQIA+CROP	2	7B	0.670	0.875	0.677	0.181	0.690	0.649	4.1%
+CQIA+CROP	4	7B	0.709	0.910	0.704	0.227	0.717	0.686	3.1%
InternLM2-Base	N/A	7B	0.368	0.445	0.381	0.148	0.409	0.327	8.2%
+CQIA+CROP	1	7B	0.764	0.942	0.787	0.276	0.770	0.757	3.3%
+CQIA+CROP	2	7B	0.809	0.909	0.855	0.414	0.811	0.807	0.4%
+CQIA+CROP	4	7B	0.768	0.939	0.794	0.285	0.770	0.766	0.4%