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Building a Family of Data Augmentation Models for Low-cost LLM Fine-tuning on the Cloud

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Motivation

In order to spetialize LLMs in specific domains or tasks,

- The construction and annotation of datasets are **costly**.
- **Open-source models** have become strong enough to handle dataset construction in many scenarios.

We present a family of data augmentation models designed to significantly improve the efficiency for model fine-tuning.

- **Prompt Refinement**
- **Prompt Expansion**

Tasks

Prompt Refinement:

- Rewrite prompts to enable LLMs to generate more helpful responses.

Original	Create a travel guide for Hangzhou.
Refined	Create a comprehensive Hangzhou travel guide containing key information. The guide should include: 1. Introduction and recommended itinerary for major attractions in Hangzhou. 2. Recommended local foods and restaurant information. 3. Accommodation suggestions, including options for different budget levels. 4. Local transportation guide, including how to get from the airport to the city center and recommended transportation between attractions. 5. Visitor tips, such as the best travel seasons, local cultural etiquette, etc. Based on the above requirements, please create a complete Hangzhou travel guide.

Tasks

Prompt Expansion:

- To generate new instructions with **similar task** types, but **different semantic** information.

Example Input

> *"Plan an in depth tour itinerary of France that includes Paris, Lyon, and Provence."*

Example Output 1

> *"Describe a classic road trip itinerary along the California coastline in the United States."*

Example Output 2

> *"Create a holiday plan that combines cultural experiences in Bangkok, Thailand, with beach relaxation in Phuket."*

Well-curated dataset for training

Dataset Diversity:

- Balanced task re–sampling
- Balanced language distribution (EN & CH)
- Various data sources

Automatic Annotation:

- Well–curated annotation prompt.
- Human annotated in–context examples

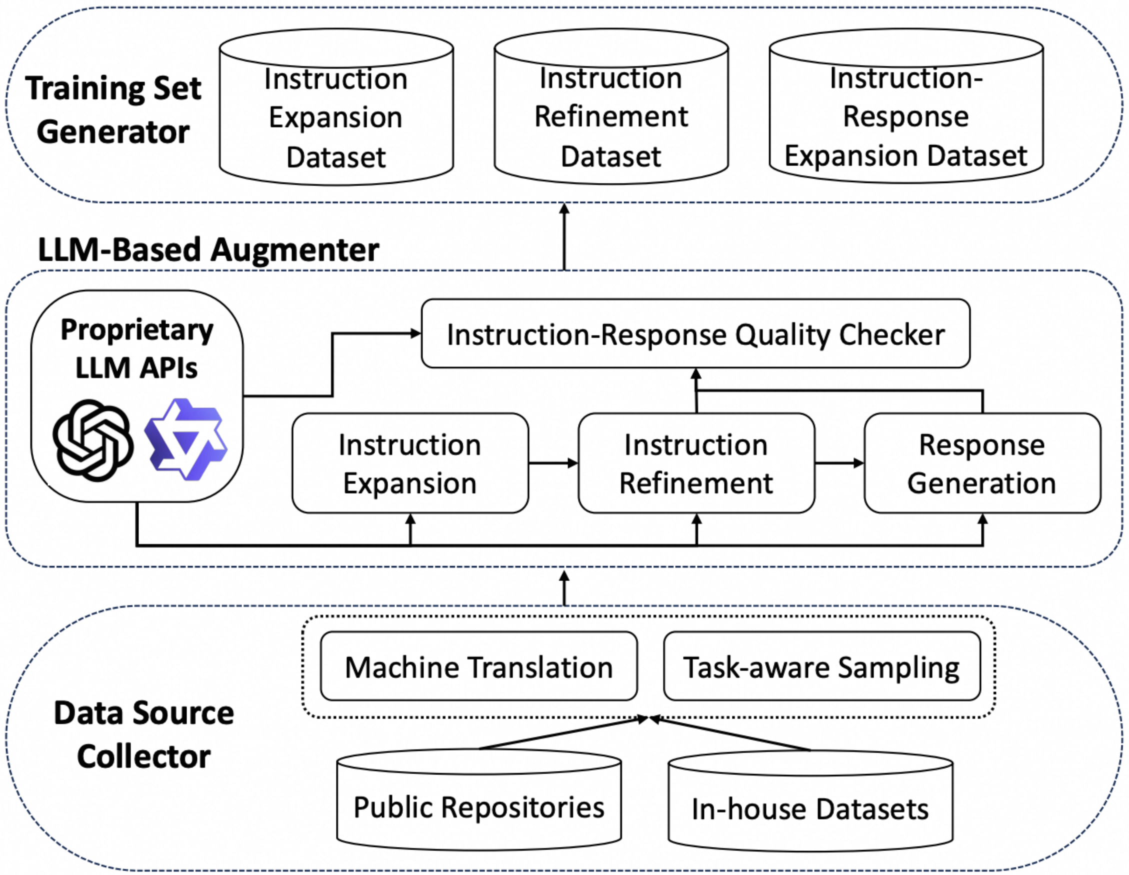


Figure 1: The data collection system.

Experiments

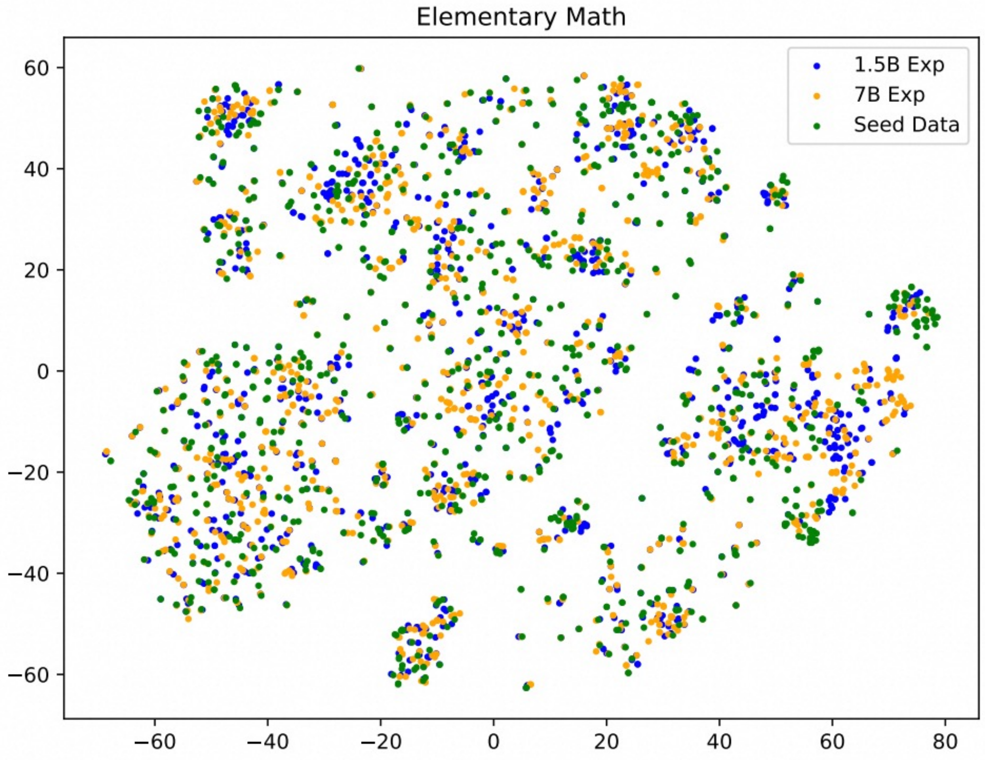
Model	Detail	Truthfulness
Qwen2-1.5B-Instruct	50.00%	50.00%
+ *Qwen2-1.5B-Instruct-Refine*	75.63%	63.75%
+ *Qwen2-7B-Instruct-Refine*	76.56%	62.19%
Qwen2-7B-Instruct	50.00%	50.00%
+ *Qwen2-1.5B-Instruct-Refine*	70.94%	57.19%
+ *Qwen2-7B-Instruct-Refine*	74.69%	58.44%

Table 5: The relative win rate of our IR models in terms of level of details and truthfulness relative to original instructions with two different response LLMs.

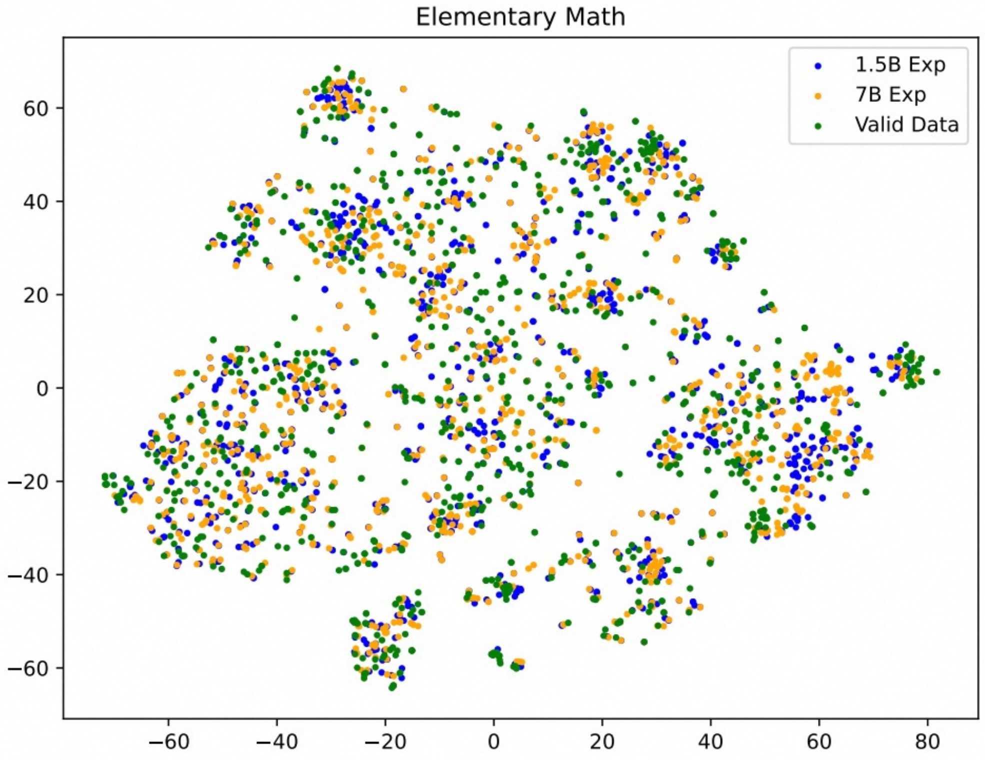
Model	Math	Impl.
Qwen2-1.5B-Instruct	57.90%	28.96%
+ *Qwen2-1.5B-Instruct-Exp*	59.15%	31.22%
+ *Qwen2-7B-Instruct-Exp*	58.32%	39.37%
Qwen2-7B-Instruct	71.40%	28.85%
+ *Qwen2-1.5B-Instruct-Exp*	73.90%	35.41%
+ *Qwen2-7B-Instruct-Exp*	72.53%	32.92%

Table 4: Effectiveness of IE models on two challenging tasks.

Experiments



(a) Visualization of t-SNE dimensionality reduction for the expanded data and the original seed data.



(b) Visualization of t-SNE dimensionality reduction for the expanded data and the validation data.

Deploy to cloud services

- We have deployed the models on the Alibaba Cloud Platform.
- Users can start servers to perform model inference with just one click.

Try our models on HuggingFace

Limitations:

- The improvements of our model's prompt re-writing are quite marginal on super powerful LLMs, such as GPT-4.
- Our models are not good at irregular prompts, such as extremely long prompts.

Models are publicly available on Huggingface!

- https://huggingface.co/alibaba-pai/Qwen2-7B-Instruct-Refine
- https://huggingface.co/alibaba-pai/Qwen2-7B-Instruct-Exp

Thanks!

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