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Knowledge-to-SQL: Enhancing SQL Generation with Data Expert LLM

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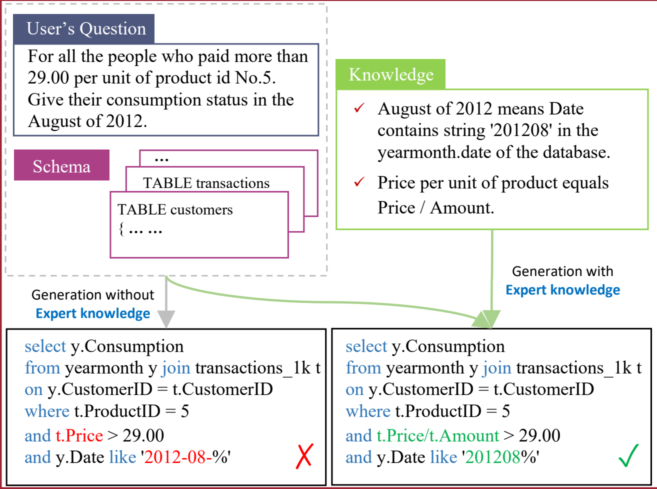
Introduction



- The text-to-SQL task involves converting natural language question into executable SQL query.
- Given challenging questions and complex database structures, LLMs often make mistakes without sufficient specialized knowledge.
- Incorporating "Expert Knowledge" linking domain-specific content with the database and question can help.
- We propose a novel framework that can generate the required knowledge to assist in accurate SQL generation.

Training Details of Data Expert LLM (DELLM)

- **Supervised Fine-tuning of DELLM:** Firstly, the model is SFT based on the gold knowledge annotated by human experts, which can generate helpful knowledge preliminarily.
  - To enhance the model understanding, the input of SFT training incorporates the relevant table T for the user question Q in the corresponding database S.
  - Given human-annotated knowledge K^{gold} as the training label, the objective function of SFT is:

$$\mathcal{L}_{SFT} = -\log \Pr(K^{gold} \mid Q, S, T) = -\sum K^{gold} \log(K^{gen})$$

- **Preference Learning via Database Feedback:** Secondly, the model is further refined by PL based the feedback from the database's execution and the knowledge contribution to the ground-truth SQL.
  - The gold and generated knowledge are denoted by K^{gold} and K^{gen}, respectively. The execution result of the ground-truth SQL Y and the SQL generated by incorporating K^{gen} are denoted by V^{gold} and V^{gen}. We obtain the preference knowledge pairs K_w, K_l through indicator χ_{db} that evaluates the execution results and χ_{sql} that measures the contribution of the knowledge:

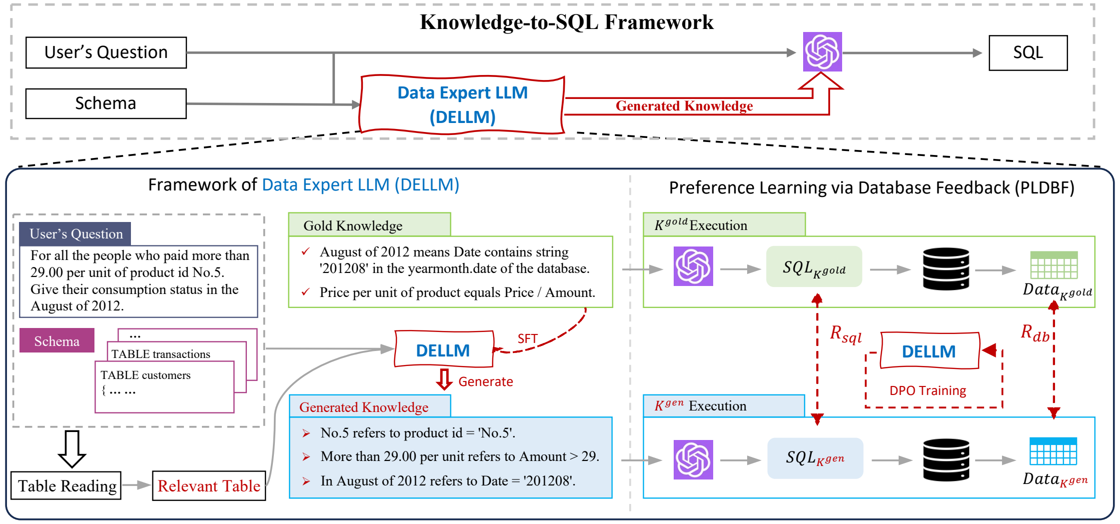
$$\mathcal{P}^{db}_{\{K_w,K_l\}} = \{K^{gold}, K^{gen} \mid \chi_{db}(V^{gold}, V^{gen}) = 0\}$$

$$\mathcal{P}^{sql}_{\{K_w,K_l\}} = \{K^{gold}, K^{gen} \mid \chi_{sql}(K^{gold}, Y) = 1, \chi_{sql}(K^{gen}, Y) = 0\}$$

  - Then, the DPO training is conducted as further preference learning refinement:

$$\mathcal{L}_{\mathrm{PL}}(\pi^{DPO}; \pi^{SFT}) = -\mathbb{E}_{\pi}[\log \sigma(\beta R(K_w) - \beta R(K_l))]$$

Proposed Method



- **SFT**: Supervised Fine-tunes the DELLM based on enhanced input and human-annotated knowledge.
- **PLDBF**: Optimizes knowledge generation through preference learning with database feedback.
- **Knowledge-to-SQL**: Integrates generated knowledge to assist an off-the-shelf text-to-SQL model, significantly improving the accuracy.

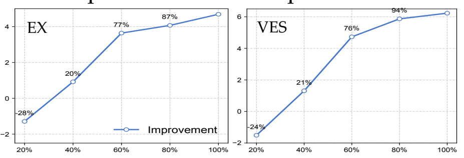
Experiments

	Models	EX		VES	
		w/o knowledge	w/ DELLM	w/o knowledge	w/ DELLM
BIRD	T5-3B	10.37	16.68 (+6.31)	13.62	20.84 (+7.22)
BIRD	GPT-3.5-Turbo	27.64	33.31 (+5.67)	28.64	36.12 (+7.48)
BIRD	GPT-4	33.25	37.94 (+4.69)	35.92	42.15 (+6.23)
BIRD	Claude-2	30.05	35.53 (+5.48)	32.97	39.71 (+6.74)
BIRD	GPT-3.5-Turbo + CoT	27.25	32.79 (+5.54)	29.16	35.51 (+6.35)
BIRD	DAIL-SQL + GPT-4	40.89	45.81 (+4.92)	45.13	51.59 (+6.46)
BIRD	MAC-SQL + GPT-4	43.65	48.92 (+5.27)	48.07	54.78 (+6.71)
Spider	GPT-3.5-Turbo	67.89	69.60 (+1.71)	68.33	70.16 (+1.83)
Spider	GPT-4	70.02	71.68 (+1.66)	71.03	72.82 (+1.79)

- The improvement brought by DELLM to different methods on Spider and BIRD

Model	Simp.	Mod.	Chall.	All
GPT-3.5-Turbo	35.58	14.60	17.61	27.64
GPT-3.5-Turbo + D	43.09	18.30	17.61	33.31
GPT-3.5-Turbo + E	50.27	31.81	20.42	41.98
GPT-4	41.05	21.13	21.13	33.25
GPT-4 + D	47.16	24.18	21.83	37.94
GPT-4 + E	54.01	36.38	31.69	46.67

- Compared to human expert annotations



- Performance on partial training data

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- Code: https://github.com/Rcrossmeister/Knowledge-to-SQL Paper: https://arxiv.org/pdf/2402.11517