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A Warm-up Dataset

For the warm-up training of the tuneable rewriter, we construct a pseudo dataset for the query rewriting task. For benchmarks that provide official training and test splits (HotpotQA and AmbigNQ), we use the whole training set. For those that have no official splits (PopQA and MMLU), we randomly split the full dataset. In detail, PopQA contains 16 types of questions, thus split into 13k for training and 714 for testing following stratified sampling. For MMLU, each of the 4 categories is randomly split into 80% for the training set and 20% for the test set. Then the training sets of each benchmark are used to derive the pseudo dataset for the query rewriting, i.e., $D_{Train} = \{(x, \tilde{x}) | \hat{y} = y\}$. We present the statistics of the splits and warm-up dataset in Table 5.

Task	Training Set	Warm-up	Test Set
HotpotQA	90.4k	37.5k	7.4k
AmbigNQ	19.4k	8.6k	1k
PopQA	13.0k	6.0k	0.7k
Humanities	3.8k	1.5k	0.9k
STEM	2.4k	0.9k	0.6k
Other	2.6k	1.3k	0.6k
Social Science	2.4k	1.3k	0.6k

Table 5: Metrics of multiple choice QA.

B Setup Details

For warm-up, we train the T5-large with 3e-5 learning rate, {16, 20} batch size, for {6,8,12} epochs. For reinforcement learning, we set the sampling steps to 5120, 10 threads, 512 steps for each. After sampling, the policy network is trained for {2,3,4} epochs, with learning rate as 2e-6 and batch size as {8,16}. λ_f and λ_h are 1.0. β in Eq. 4 is dynamically adapted according to Ramamurthy et al. (2022); Ziegler et al. (2019),

$$e_t = \text{clip}\left(\frac{\text{KL}\left(\pi \| \pi_0\right) - \text{KL}_{\text{target}}}{\text{KL}_{\text{target}}}, -0.2, 0.2\right),$$
$$\beta_{t+1} = \beta_t \left(1 + \text{K}_\beta e_t\right),$$

where KL_{target} is set to 0.2, K_β is set to 0.1. β_0 is initialized to be 0.001. The generation strategy follows the 4-beam search and returns the one sequence. In the implementation of the BM25-based retriever, the textboxes from searched URLs are parsed from HTML code. We compute BM25 scores between the paragraph from each textbox and the query following the scikit-learn package, then keep those with higher scores until the reserved context reaches a max length. In reinforcement learning, the results of AmbigNQ are with the BM25 method, while others use snippets as context.

C Web Search: Tool Use

Our proposed pipeline integrates an externally built web search engine as the retriever module. We present more discussion on the advantages and disadvantages here.

The usage of external tools expands the ability boundary of language models, compensating for the parametric knowledge, and grounding the capabilities of language models to interact with environments (Qin et al., 2023; Schick et al., 2023). Recent studies show a trend to leverage plug-and-play tools like search engines to enhance language agents (Lazaridou et al., 2022; Menick et al., 2022; Shuster et al., 2022; Shen et al., 2023). Search engine APIs are well-developed retrievers, saving efforts to build and maintain another retriever, like a Contriever. Accessible to the whole Internet, the web search retrieves from a wide-range, up-to-date