Decomposed Prompting: A Modular Approach for Solving Complex Tasks
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## ssues:

- Sub-tasks can be too hard to be learned from just CoT prompting
- Certain sub-tasks are better performed by existing tools (e.g., calculation)

Solution: Decompose tasks into sub-tasks which are solved by specialized handlers ("tools") Decomposer: Q => decomposition into simpler sub-task

- Sub-Task Handlers: Library of sub-task specific tools (LLMs, APIs, etc)



## DecomP: Letter Concatenation


solit

A: ["Augusta", "Ada", "King"]
$\stackrel{A}{A} \cdot:$

## merge

a: Concatenate ["a", "a", "g"] using a space, A: "a ag"

DecomP Inference: Iterative Generation


Key Difference
A task-independent approach that can use rich structure with any number of tools and only requires few-shot prompting to iteratively decompose any task

## $? \rightarrow$ 绨 <br> $\frac{\text { Wikipedia Title: Mack Rides }}{\text { Mack Rides GmbH \& Co }}$ <br> Wack Rides GmbH \& $\mathrm{Co} \ldots$ Q: Which company manufactured The Lost Gravity? | $\begin{array}{l}\text { Lost Gravity? } \\ \text { A: "Mack Rides" }\end{array}$ singlehop_rcqa |
| :--- |

## Approaches for Multi-step Reasonin

Task-Specific Approaches: WebGPT (Nakano et al., '21), SelfAsk (Press et al.,'22), IRCoT (Trivedi et al.,'22), inter alia.
Fixed Structure: Least-to-most (Zhou et al., '22), Successive Prompting (Dua et al.,'22), inter alia.
Require Fine-Tuning: TMNs (Khot et al.,'21), ReAct*(Yao et al.,'22), Toolformer (Schick et al.,'23), inter alia
Program Generation: PAL (Gao et al.,'22), Pot (Chen et al.,'22), inter

## Related Work

Better generalization than CoT and Least-to-Most prompting


More effective than retrieve-read models
Effective with smaller models too

$\square$ No-Cxt QA $\square$ NoDecomp-Ctxt QA Decomp-Ctxt QA

$\underset{\text { Stony Brook }}{*}$


Ai2

