NEURAL INFORMATION PROCESSING SYSTEMS
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# Chameleon: Plug-and-Play Compositional Reasoning with Large Language Models

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https://chameleon-llm.github.io

## Tool-Augmented LLMs

Hugging Face, Bing, OpenAI, GitHub, Bard AI, Google, python, OpenAI DALL·E 3

How to **compose** these numerous tools to tackle complex tasks?

## Chameleon on ScienceQA and TabMWP

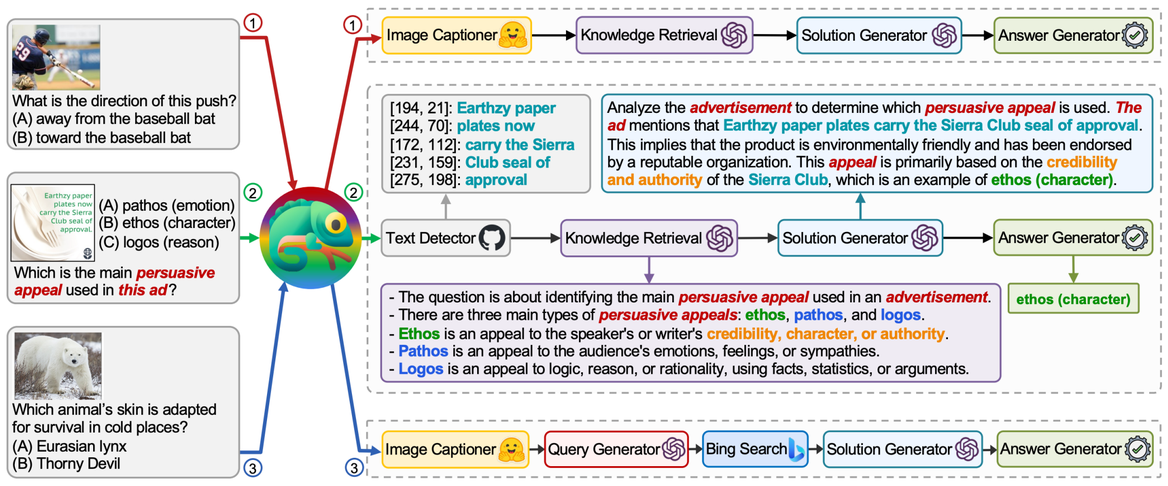



Figure 1: Examples from our **Chameleon** approach with GPT-4 on ScienceQA [28], a multi-modal question answering benchmark in scientific domains. **Chameleon** is adaptive to different queries by synthesizing programs to compose various tools and executing them sequentially to get final answers.

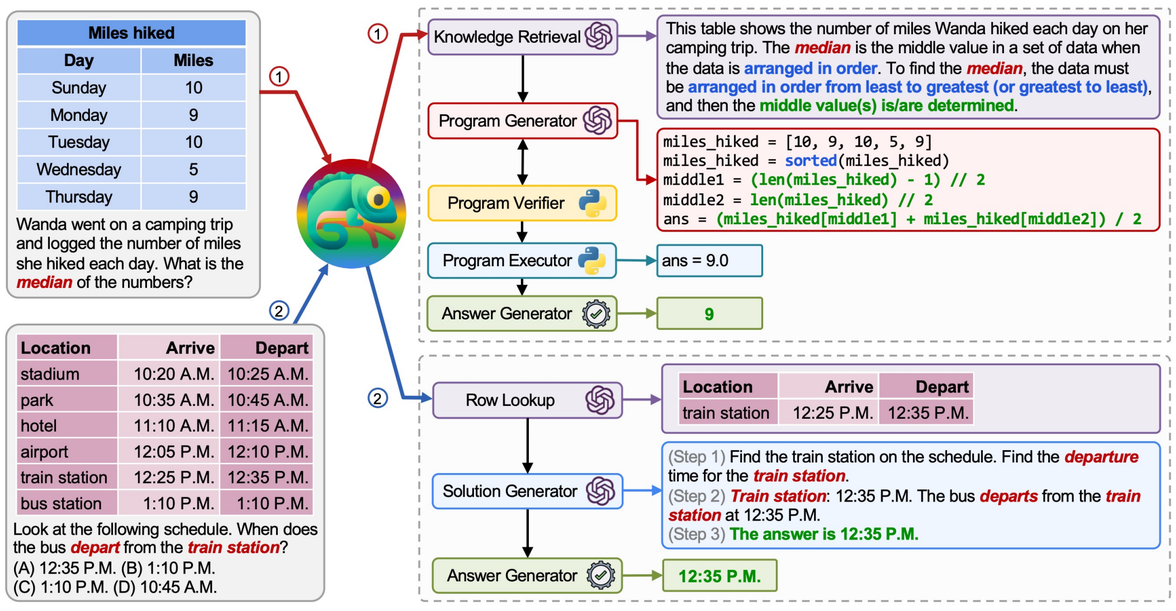



Figure 2: Two examples from our **Chameleon** approach with GPT-4 on TabMWP [29], a mathematical reasoning benchmark with tabular contexts. **Chameleon** demonstrates flexibility and efficiency in adapting to different queries that require various reasoning abilities.

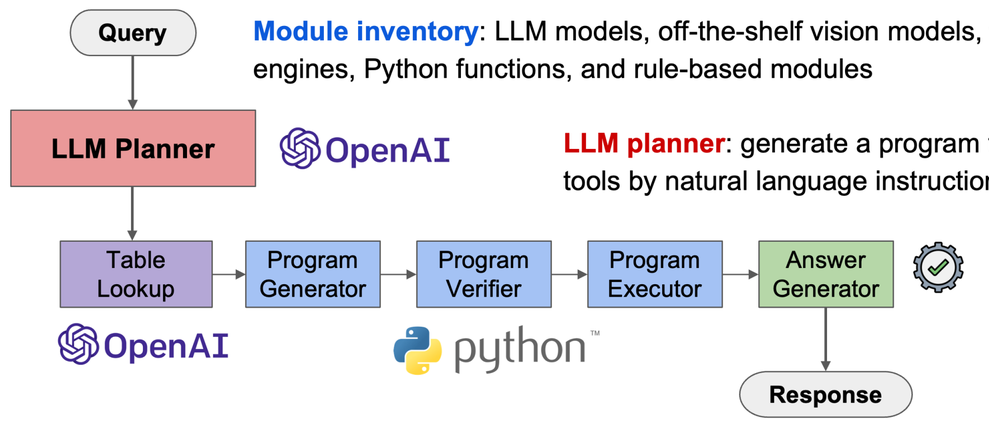
## Experiments on ScienceQA

| Model | #Tuned Params | ALL | NAT | SOC | LAN | TXT | IMG | NO | G1-6 | G7-12 |
|---|---|---|---|---|---|---|---|---|---|---|
| *Heuristic baselines* | | | | | | | | | | |
| Random Choice [28] | - | 39.83 | 40.28 | 46.13 | 29.25 | 47.45 | 40.08 | 33.66 | 39.35 | 40.67 |
| Human [28] | - | 88.40 | 90.23 | 84.97 | 87.48 | 89.60 | 87.50 | 88.10 | 91.59 | 82.42 |
| *Fine-tuned models* | | | | | | | | | | |
| Patch-TRM [30] | 90M | 61.42 | 65.19 | 46.79 | 65.55 | 66.96 | 55.28 | 64.95 | 58.04 | 67.50 |
| VisualBERT [23, 24] | 111M | 61.87 | 59.33 | 69.18 | 61.18 | 62.71 | 62.17 | 58.54 | 62.96 | 59.92 |
| UnifiedQA [18] | 223M | 70.12 | 68.16 | 69.18 | 74.91 | 63.78 | 61.38 | 77.84 | 72.98 | 65.00 |
| UnifiedQA CoT [28] | 223M | 74.11 | 71.00 | 76.04 | 78.91 | 66.42 | 66.53 | 81.81 | 77.06 | 68.82 |
| MM-COT [60] | 223M | 84.91 | 87.52 | 77.17 | 85.82 | 87.88 | 82.90 | 86.83 | 84.65 | 85.37 |
| MM-COT$_{Large}$ [60] | 738M | 91.68 | 95.91 | 82.00 | 90.82 | 95.26 | 88.80 | 92.89 | 92.44 | 90.31 |
| LLaMA-Adapter$_T$ [59] | 1.2M | 78.31 | 79.00 | 73.79 | 80.55 | 78.30 | 70.35 | 83.14 | 79.77 | 75.68 |
| LLaMA-Adapter [59] | 1.8M | 85.19 | 84.37 | 88.30 | 84.36 | 83.72 | 80.32 | 86.90 | 85.83 | 84.05 |
| *Few-shot GPT-3* | | | | | | | | | | |
| GPT-3 [3] | 0M | 74.04 | 75.04 | 66.59 | 78.00 | 74.24 | 65.74 | 79.58 | 76.36 | 69.87 |
| GPT-3 CoT [28] | 0M | 75.17 | 75.44 | 70.87 | 78.09 | 74.68 | 67.43 | 79.93 | 78.23 | 69.68 |
| Published results (Above) ▲ | | | | | | | | | | |
| *Few-shot ChatGPT* | | | | | | | | | | |
| ChatGPT CoT | 0M | 78.31 | 78.82 | 70.98 | 83.18 | 77.37 | 67.92 | 86.13 | 80.72 | 74.03 |
| **Chameleon (ChatGPT)** | 0M | 79.93 | 81.62 | 70.64 | 84.00 | 79.77 | 70.80 | 86.62 | 81.86 | 76.53 |
| *Few-shot GPT-4* | | | | | | | | | | |
| GPT-4 CoT | 0M | 83.99 | 85.48 | 72.44 | 90.27 | 82.65 | 71.49 | 92.89 | 86.66 | 79.04 |
| **Chameleon (GPT-4)** | 0M | **86.54** | **89.83** | **74.13** | **89.82** | **88.27** | **77.64** | **92.13** | **88.03** | **83.72** |

## Experiments on TabMWP

| Model | #Tuned Params | ALL | FREE | MC | INT | DEC | EXTR | BOOL | OTH | G1-6 | G7-8 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| *Heuristic baselines* | | | | | | | | | | | |
| Heuristic guess | - | 15.29 | 6.71 | 39.81 | 8.37 | 0.26 | 30.80 | 51.22 | 26.67 | 17.55 | 12.27 |
| Human performance | - | 90.22 | 84.61 | 93.32 | 84.95 | 83.29 | 97.18 | 88.69 | 96.20 | 94.27 | 81.28 |
| *Fine-tuned models* | | | | | | | | | | | |
| UnifiedQA$_{BASE}$ [18] | 223M | 43.52 | 34.02 | 70.68 | 40.74 | 7.90 | 84.09 | 55.67 | 73.33 | 53.31 | 30.46 |
| UnifiedQA$_{LARGE}$ [18] | 738M | 57.35 | 48.67 | 82.18 | 55.97 | 20.26 | 94.63 | 68.89 | 79.05 | 65.92 | 45.92 |
| TAPEX$_{BASE}$ [25] | 139M | 48.27 | 39.59 | 73.09 | 46.85 | 11.33 | 84.19 | 61.33 | 69.52 | 56.70 | 37.02 |
| TAPEX$_{LARGE}$ [25] | 406M | 58.52 | 51.00 | 80.02 | 59.92 | 16.31 | 95.34 | 64.00 | 73.33 | 67.11 | 47.07 |
| *Zero-shot GPT-3* | | | | | | | | | | | |
| GPT-3 [3] | 0M | 56.96 | 53.57 | 66.67 | 55.55 | 45.84 | 78.22 | 55.44 | 54.29 | 63.37 | 48.41 |
| GPT-3 CoT [53] | 0M | 57.61 | 54.36 | 66.92 | 55.82 | 48.67 | 78.82 | 55.67 | 51.43 | 63.62 | 49.59 |
| *Few-shot GPT-3* | | | | | | | | | | | |
| GPT-3 [3] | 0M | 57.13 | 54.69 | 64.11 | 58.36 | 40.40 | 75.95 | 52.41 | 53.02 | 63.10 | 49.16 |
| GPT-3 CoT [53] | 0M | 62.92 | 60.76 | 69.09 | 60.04 | 63.58 | 76.49 | 61.19 | 67.30 | 68.62 | 55.31 |
| GPT-3 CoT-PromptPG [29] | 0M | 68.23 | 66.17 | 74.11 | 64.12 | 74.16 | 76.19 | 72.81 | 65.71 | 71.20 | 64.27 |
| Codex PoT* [5] | 0M | 73.2 | - | - | - | - | - | - | - | - | - |
| Codex PoT-SC* [5] | 0M | 81.8 | - | - | - | - | - | - | - | - | - |
| Published results (Above) ▲ | | | | | | | | | | | |
| *Few-shot ChatGPT* | | | | | | | | | | | |
| ChatGPT CoT | 0M | 82.03 | 78.43 | 92.32 | 75.38 | 90.30 | 92.30 | 92.89 | 87.62 | 83.06 | 80.66 |
| ChatGPT PoT | 0M | 89.49 | 90.24 | 87.35 | 89.31 | 93.82 | 92.10 | 85.89 | 55.24 | 90.60 | 88.00 |
| **Chameleon (ChatGPT)** | 0M | 93.28 | 93.13 | 93.72 | 92.71 | 94.76 | 91.29 | 98.11 | 78.85 | 93.37 | 93.17 |
| *Few-shot GPT-4* | | | | | | | | | | | |
| GPT-4 CoT | 0M | 90.81 | 88.48 | 97.49 | 86.16 | 97.51 | 96.86 | 99.11 | 89.52 | 92.40 | 88.70 |
| GPT-4 PoT | 0M | 96.93 | 97.40 | 95.58 | 98.48 | 93.22 | 96.25 | 98.00 | 68.57 | 96.97 | 96.87 |
| **Chameleon (GPT-4)** | 0M | **98.78** | **98.95** | **98.29** | **99.34** | **97.42** | **98.58** | **98.56** | **93.33** | **98.95** | **98.54** |

## Chameleon: LLM Planner




**Module inventory**: LLM models, off-the-shelf vision models, web search engines, Python functions, and rule-based modules

**LLM planner**: generate a program to compose tools by natural language instructions

### Advantages

- Efficiently **extendable** to using new modules
- **Natural-language-like programs** are less error-prone, easy to debug, & user-friendly
- **Flexible to replace** the underlying LLM for the planner as well as each module

You need to act as a policy model, that given a question and a modular set, determines the sequence of modules that can be executed sequentially to solve the query.

The modules are defined as follows:

**Query_Generator**: This module generates a search engine query for the given question. Normally, we consider using "Query_Generator" when the question involves domain-specific knowledge.

**Bing_Search**: This module searches the web for relevant information to the question. Normally, we consider using "Bing_Search" when the question involves domain-specific knowledge.

**Image_Captioner**: This module generates a caption for the given image. Normally, we consider using "Image_Captioner" when the question involves the semantic understanding of the image, and the "has_image" field in the metadata is True.

**Text_Detector**: This module detects the text in the given image. Normally, we consider using "Text_Detector" when the question involves the unfolding of the text in the image, e.g., diagram, chart, table, map, etc., and the "has_image" field in the metadata is True.

**Knowledge_Retrieval**: This module retrieves background knowledge as the hint for the given question. Normally, we consider using "Knowledge_Retrieval" when the background knowledge is helpful to guide the solution.

**Solution_Generator**: This module generates a detailed solution to the question based on the information provided. Normally, "Solution_Generator" will incorporate the information from "Query_Generator", "Bing_Search", "Image_Captioner", "Text_Detector", and "Knowledge_Retrieval".

**Answer_Generator**: This module extracts the final answer in a short form from the solution or execution result.

Below are some examples that map the problem to the modules.

**Question**: Compare the average kinetic energies of the particles in each sample. Which sample has the higher temperature?

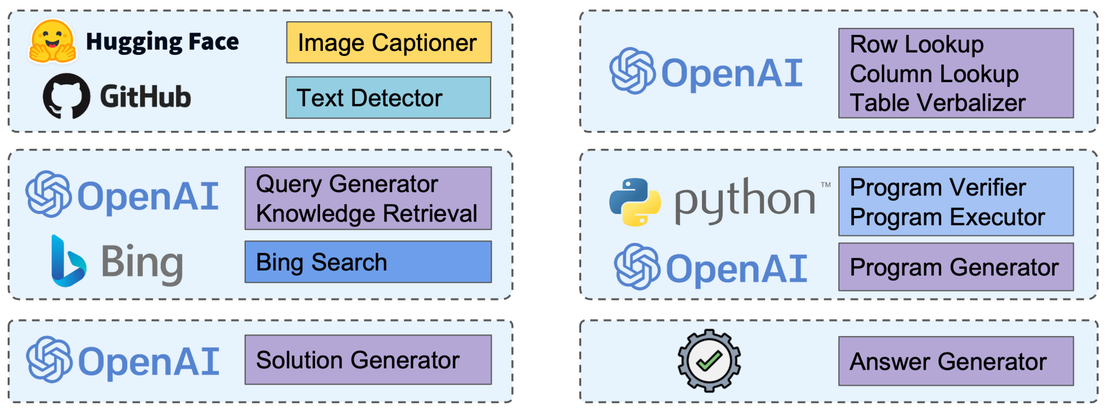
**Context**: The diagrams below show two pure samples of gas in identical closed, rigid containers. Each colored ball represents one gas particle. Both samples have the same number of particles.

**Options**: (A) neither; the samples have the same temperature (B) sample A (C) sample B

**Metadata**: 'pid': 19, 'has_image': True, 'grade': 8, 'subject': 'natural science', 'topic': 'physics', 'category': 'Particle motion and energy', 'skill': 'Identify how particle motion affects temperature and pressure'

**Modules**: ["Text_Detector", "Knowledge_Retrieval", "Solution_Generator", "Answer_Generator"]

## Chameleon: Module Inventory




## Tool Use Planning

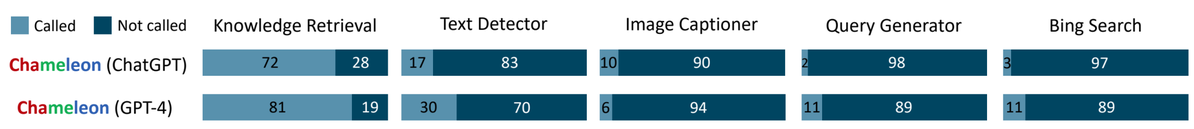



Figure 4: Tools called in the generated programs from **Chameleon** on ScienceQA.

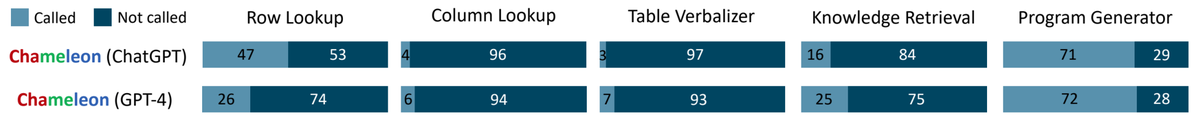



Figure 5: Tools called in the generated programs from **Chameleon** on TabMWP.

## Transition Graph for Generated Programs

- Transition graphs of modules for generated programs by Chameleon (GPT-4)
- Transition probabilities are computed from tool transitions observed on the test sets
- GPT-4 planner **makes good decisions on how to sequence tools**