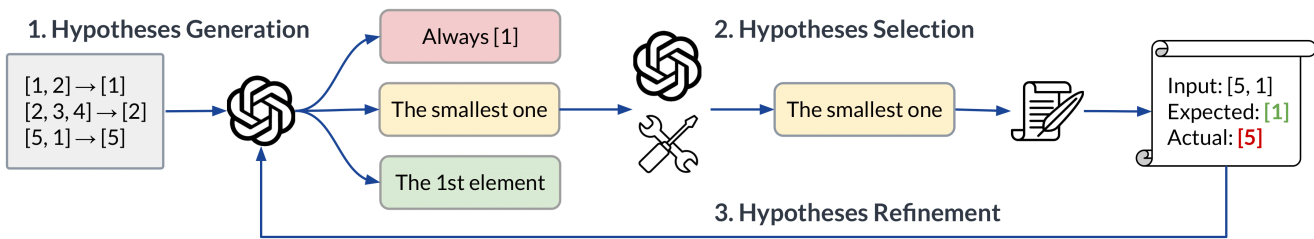


LLM Inductive Reasoning

This repository contains code for the paper "[Phenomenal Yet Puzzling: Testing Inductive Reasoning Capabilities of Language Models with Hypothesis Refinement](#)"

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	ACRE	MiniSCAN	List Functions	MiniARC
Examples				
Bad Rule			The smallest one	Swap the colors of two objects
Good Rule			The 1st element	Drop all objects

Setup

1. Set up the OpenAI API key and Anthropic API key. Store them in the environment variables `OPENAI_API_KEY` and `ANTHROPIC_API_KEY`.
2. Install the dependencies using

```
pip install -r requirements.txt
```

Code Structure

- `data`: Data used in our paper.
- `prompts`: Prompt templates for each task.
- `tasks`: Task-specific code.
- `outputs`: Outputs and model interactions for each task. The naming convention follows `{model}_{dataset}_{method}_iter{max_iter}_t{temperature}_n{n}_{rule_type}_{interpreter_type}.json` (see below). The default setting is used if a value is not specified.
- `scripts`: Useful scripts.

Run Experiments

To rerun our experiments, you'll need access to the relevant APIs. You can also convert our provided output files into a cache file. Our query function will automatically use the cache content without making API calls. You should be able to roughly reproduce all of our experiments this way, except for some experiments where the translated Python programs introduce some randomness. To convert outputs to a cache file, run:

```
python scripts/convert_outputs_to_cache.py \
  --output_dir outputs \
  --cache_file outputs/query_cache.pkl
```

All experiments can be run using `python run_task.py`. You may need to specify the following key arguments:

- `--data_file`: Path to the data JSONL file. The data used in our paper is in `data` directory.
- `--model_name`: Model name, choices=([`gpt-4-0613`, `gpt-3.5-turbo-0613`, `claude-2`, `Meta-Llama-3-8B-Instruct`, `Meta-Llama-3-70B-Instruct`]).
- `--task_name`: Task name, choices=([`acre`, `scan`, `list_function`, `arc`]).
- `--output_file`: Path for the output JSON file.
- `--method`: Method, choices=([`rule`, `io`]).
- `--max_iter`: Maximum number of iterations.
- `--temperature`: Sampling temperature.
- `--n`: Number of outputs per API call, i.e., the number of hypotheses per iteration for rule prompting and the number of predictions for SC prompting.
- `--rule_type`: Representation of hypothesis (see Section 2.2 of the paper).
- `--interpreter_type`: Type of interpreter, choices=([`default`, `lm`]).
- `--n_train`: Number of seen examples for each task.
- `--n_test`: Number of unseen examples for each task.
- `--cache_file`: Path to the cache file. It should be the same as the one used in `scripts/convert_outputs_to_cache.py`. Default to `${output_dir}/query_cache.pkl` if not specified.
- `--history_file`: Path to the history file that will be used to store the history of interactions with the model. Default to `${output_dir}/history.jsonl` if not specified.

For running Meta-Llama-3-8B-Instruct and Meta-Llama-3-70B-Instruct, you should install `vllm`, and `openai==1.35`.

You should first deploy the Meta-Llama-3-8B-Instruct or Meta-Llama-3-70B-Instruct model

```
# For Meta-Llama-3-70B-Instruct 2 A100 80G
python -m vllm.entrypoints.openai.api_server --model Meta-Llama-3-70B-Instruct --tensor-parallel-size 2
# For Meta-Llama-3-8B-Instruct 2 A100 80G
python -m vllm.entrypoints.openai.api_server --model Meta-Llama-3-8B-Instruct --tensor-parallel-size 2
```

The follow the steps below:

To run experiments using iterative hypothesis refinement:

```
python run_task.py --data_file ${data_file} \  
  --model_name ${model_name} \  
  --task_name ${task} \  
  --output_file ${output_file} \  
  --max_iter ${iter} --temperature ${t} --n ${n}
```

To run experiments using input-output (IO) prompting:

```
python run_task.py --data_file ${data_file} \  
  --model_name ${model_name} \  
  --task_name ${task} \  
  --output_file ${output_file} \  
  --method io
```

To run experiments using self-consistency (SC) prompting:

```
python run_task.py --data_file ${data_file} \  
  --model_name ${model_name} \  
  --task_name ${task} \  
  --output_file ${output_file} \  
  --method io \  
  --temperature ${t} --n ${n}
```

To run experiments using Self-Refine (SR):

```
python run_task.py --data_file ${data_file} \  
  --model_name ${model_name} \  
  --task_name ${task} \  
  --output_file ${output_file} \  
  --max_iter ${iter} --temperature ${t} --n ${n} \  
  --rule_type "nl" \  
  --interpreter_type "lm"
```

To apply existing induced rules using LMs (see Section 4.1):

```
python eval_task.py --data_file ${dta_file} \  
  --model_name ${model_name} \  
  --task_name ${task} \  
  --method io
```

```
--input_file ${input_file} \  
--output_file ${output_file}
```

How to Add a New Task

To setup your own task:

1. Convert your data into a JSONL file, with each line representing one example. Each example should follow:

```
{  
  "train": [  
    {"input": "input_1", "output": "output_1"},  
    {"input": "input_2", "output": "output_2"},  
  ],  
  "test": [  
    {"input": "input_3", "output": "output_3"},  
    {"input": "input_4", "output": "output_4"},  
  ]  
}
```

2. Add your prompt templates into `prompts/${task_name}.py`. You need to define the following prompt templates:

```
io_prompt = ""  
example_prompt = ""  
rule_prompt = ""  
feedback_prompt = ""  
rule_with_feedback_prompt = ""  
rule_to_output_prompt = ""
```

3. Add your task to `tasks/${task_name}.py` by inheriting from `Task` in `tasks/base.py`. At a minimum, you need to implement the `apply_all_rules` function. If you use an LM interpreter, this function can simply be `apply_all_rules_with_lm`. If you use a Python interpreter, you can inherit directly from `PythonTask` in `tasks/base.py`.