Zindi ARC Challenge: A Week-Long Sprint Towards Conditioned Reasoning

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1 Background

The ARC (Abstraction and Reasoning Corpus),[1] introduced in 2019 by François Chollet, was designed to probe a system's capacity for fluid intelligence. It involves solving visual pattern puzzles from very limited examples — mimicking the kind of reasoning humans perform when generalizing from few demonstrations. Unlike typical machine learning (ML) benchmarks, it doesn't reward data-hungry solutions, but instead focuses on generalizable reasoning strategies.

The Zindi ARC Challenge Africa[2] serves as a simplified version of the original ARC benchmark, built to encourage creative experimentation with the original competition format.

Competition objective: Develop a machine learning model that can successfully generalize from a small number of examples to solve abstract reasoning tasks. This capability is evaluated through the ability for the model to:

- Infer underlying patterns and rules from a limited set of input-output grid pairs.
- Apply these inferred rules to a new test input grid to generate the correct output grid.
- Demonstrate "fluid intelligence," the ability to solve novel problems without relying on a vast amount of prior knowledge or training data.

Remark: It is important to acknowledge that the tasks in this Zindi competition are adapted from the original ARC-AGI dataset developed by the ARC team, which is publicly available.

While the competition organizers curated a modified version to define custom train/test splits, the core task formulations remain closely aligned with the original. As such, leveraging models that were fine-tuned on or exposed to the ARC dataset—especially if those models had access to the original public training tasks—introduces a high risk of (perhaps unintended) memorization. This compromises the intended generalization objective of the benchmark, where models are expected to reason abstractly over unseen problems rather than recall previously encountered solutions.

2 Project Objectives

This sprint explored the question: *Can domain intuition and a few LLM prompts solve complex visual reasoning tasks competitively without extensive training/fine-tuning or compute?*

I hypothesized that with careful problem analysis and handcrafted strategies, one could score up to 40-50% on this competition.

In line with the original intent of the ARC benchmark, which emphasizes solving novel tasks in an abstract manner, I further aimed to assess whether one- or few-shot prompting alone could yield competitive results—without any fine-tuning. The ultimate goal was to simulate a human-like problem-solving process: general reasoning guided by structure and analogy, rather than pattern recall.

[1] https://arcprize.org
[2] https://zindi.africa/competitions/the-arc-challenge-africa

3 Experiment

I used `Python version 3.13.5` throughout this project. The code for the solution described in this write-up is available at https://github.com/dric2018/zindi-arc-agi. The utility functions (`utils.py`) and model-specific implementations (`model.py`) can be found in the `src` folder. This folder also comprises the base prompt used as `system prompt` for LLM setup.

Overall Config

```
from   matplotlib import colors
import os
import os.path as osp
import torch

class Config:
    # I/O
    root                = "./"
    data_path           = osp.join(root, "data")
    submission_path     = osp.join(root, "submissions")
    model_zoo           = osp.join(root, "models")
    experiment          = "llm-fs"
    # 0:black, 1:blue, 2:red, 3:green, 4:yellow, # 5:gray, 6:magenta, 7:orange, 8:sky, 9:brown
    CMAP                = colors.ListedColormap(['#000000', '#0074D9', '#FF4136', '#2ECC40',
    '#FFDC00', '#AAAAAA', '#F012BE', '#FF851B', '#7FDBFF', '#870C25'])

    NORM                = colors.Normalize(vmin=0, vmax=9)
    DEFAULT_BG_VALUE    = 7  # (orange not black...from EDA)
    # model vars
    base_llm            = "Qwen/Qwen2.5-14B-Instruct"
    model_name          = "arc-solver-"+base_llm.split("/")[-1]
    device              = 'cuda'
    target_platform     = "cuda"
    dtype               = torch.float16
    to_4_bit            = True
    max_tokens          = 4096
    temperature         = 0.1
    top_p               = 0.9
    repetition_penalty  = 1.1
    do_sample           = True
    trust_remote_code   = True
    quantize_model      = True
    MAX_N               = 30
```

3.1 Day 1–2: EDA and Problem Analysis

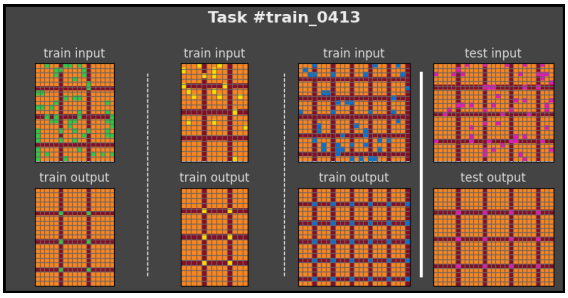
3.1.1 Setup and Tooling

- Hardware (compute capabilities): Apple M4 MBP (24GB RAM), NVIDIA RTX 6000 (48GB VRAM)
- Visualization tools extended from Kaggle starter code by Oleg X[3]
- Custom utilities for: grid parsing, data sampling, output shape inference, pixel accuracy calculation, and submission generation.

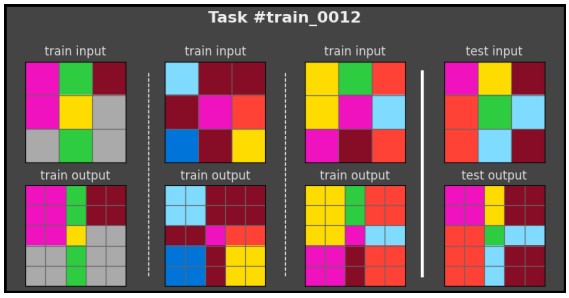
Figure 1 shows representative examples of ARC puzzles. These highlight the diverse range of tasks: from geometric symmetry and color manipulation (Fig. 1a, 1c) to pattern replication and counting-based inference

[3]https://www.kaggle.com/code/allegich/arc-agi-2025-starter-notebook-eda/notebook

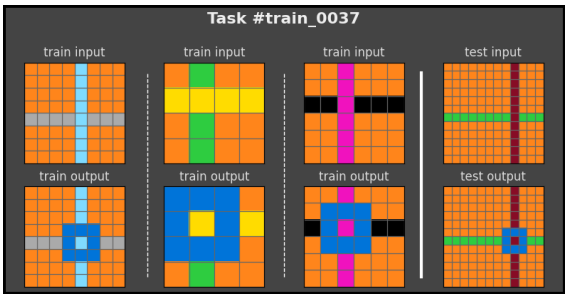
(Fig. 1b, 1d). Such diversity makes rule induction highly non-trivial and often ambiguous, motivating both analytical heuristics and perhaps LLM-based reasoning strategies.



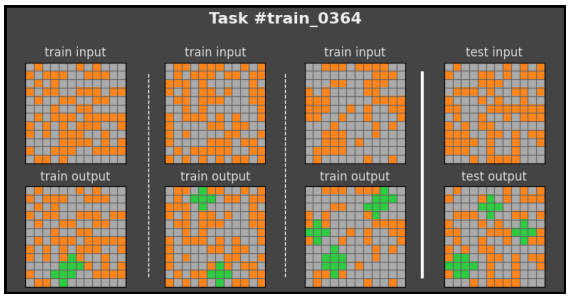
(a) Example 1



(b) Example 2



(c) Example 3



(d) Example 4

Figure 1: Examples of ARC visual puzzles from the training set. Each task consists of one or more input-output grid pairs used to infer a transformation rule, followed by a test input grid to apply that rule. Tasks vary in color schemes, layout complexity, and spatial logic.

3.1.2 Key Insights from EDA

ARC-AGI is inherently a visual reasoning challenge, where understanding spatial structures, color patterns, and transformations is essential. Thus, having effective visualization tools is crucial for meaningful exploration and analysis. While a public web application is available, developed by the authors of the original competition[4], it is not optimized for programmatic interaction or integration within experimentation pipelines. To streamline the workflow, I opted to build a custom visualization suite directly into the codebase, enabling rapid inspection, debugging, and comparative evaluation of model predictions in a notebook-friendly environment. After some exploration, I gained the following insights:

- Each task contains input-output grid pairs (up to 8 per sample), plus a test input
- Colors encoded as integers from 0 to 9 (see overall config in section 3); each grid of main size 1×1 and max size 30×30
- Background color 7 (orange) dominates the dataset; using 0 (black) for padding hurts accuracy
- Crucial design bias: test output **row count is provided** (and column count could be inferred from the sample submission), allowing constrained generation

$\longrightarrow$**Public (baseline) Score: 11.72%** (Priv. LB: 11.51%) only predicting a full orange grid with the inferred output shape.

[4] `https://github.com/fchollet/ARC-AGI/tree/master/apps`

3.2 Day 2: Heuristics and Baseline Solver

Building upon the results from the EDA stage, I implemented a fallback solver that:

- Infers output shape based on common patterns in input-output pairs
- Falls back to copying the input with the expected grid size
- Uses color frequency (mode) to pad or complete non-rectangular grids

⟶Public Score: 31.33% (Priv. LB: 30.70%)

3.3 Day 3–5: LLM Integration

I integrated large language models (LLMs) using structured few-shot prompts that describe the grid as a matrix and ask the model to return the transformed grid. Models used include:

- **Mistral-Nemo-Instruct (4bit/8bit)** — prompt compliant, fast, but limited on large inputs
- **Phi-4-mini-reasoning** — deep reasoning, but overly verbose
- **Qwen2.5-14B-Instruct** — highly performant especially on CUDA-enabled GPU, fairly accurate, and consistent

After a few trials, I kept `Qwen2.5-14B-Instruct` as my base LLM in this competition.

From a resource standpoint, the deployment of large language models (LLMs) was carefully optimized to fit within constrained hardware environments. For instance, the Qwen2.5-14B-Instruct model, when quantized to 8-bit, occupied approximately 15GB of memory on a MacBook Pro (M4) and around 21GB on an NVIDIA RTX 6000 GPU. This quantization step proved essential for enabling local inference, particularly on consumer-grade GPUs like the RTX 4090, which has a maximum of 24GB VRAM.

Despite this, the model struggled to process larger input grids (greater than 15×15) on the M4, often leading to crashes or memory exhaustion.

On the aforementioned GPU setup, a full pass over the test set typically required around two hours. Notably, all LLM experiments—including quantization, generation, and evaluation—were conducted within a budget of less than $30, making the exploration both computationally and financially feasible for a short-term hackathon setting.

Quantized Inference Setup

```
from transformers import BitsAndBytesConfig

quantization_config = BitsAndBytesConfig(
    load_in_8bit=True,
    bnb_4bit_quant_type="nf4",
    bnb_4bit_compute_dtype="float16",
    bnb_4bit_use_double_quant=True
)

llm = AutoModelForCausalLM.from_pretrained(
    base_llm_name,
    torch_dtype=Config.dtype,
    low_cpu_mem_usage=True,
    device_map="auto" if torch.cuda.is_available() else None,
    trust_remote_code   = Config.trust_remote_code,
    quantization_config=quantization_config
)
```

⟶**Best Score with LLM (pre-sealing of leaderboard): 28.85% (Priv. LB: 28.01%)**

A parsing bug that unintentionally replaced LLM predictions with background pixels limited performance during the competition. After correcting the bug, the same implementation yielded a substantial improvement of approximately **+3.5%** on the Public Leaderboard, demonstrating the underlying effectiveness of the prompting strategy.

⟶ **Post-fix Score: 32.382% (Priv. LB: 31.958%)**

3.4 Final Solution Architecture

- A shared `ARCModel` (in `src/model.py`) class handles heuristics, LLM calls, grid resizing, and evaluation
- Custom prompt defines rules for LLM task-solving using a few-shot approach
- Optional: Candidate outputs are validated using metrics (exact match, pixel accuracy)
- Final predictions are padded/cropped based on known row counts and submitted as CSV

3.4.1 Usage

Reproducing the competition score can be done by using the fallback solver through the https://github.com/dric2018/zindi-arc-agi/blob/main/zindi-arc-solver.ipynb notebook, running it from top to bottom. A summarized explanation of the procedure is also provided in the accompanying `solution.pdf` document.

Note: If executing the submission notebook on Google Colab, please follow these steps:

- Upload the https://github.com/dric2018/zindi-arc-agi/blob/main/zindi-arc-solver-colab.ipynb notebook to Colab. No GPU is required.
- After running the cell containing `!mkdir submissions src data`, upload the data and source files to their respective folders:
  - `data`
    - `train.json`
    - `test.json`
    - `SampleSubmission.csv`
  - `src`
    - `__init__.py`
    - `model.py`
    - `utils.py`
    - `config.py`
    - `base_prompt.txt`
- Update the `config.py` file by replacing the root folder path:

```
root = "/content/" # or keep it as "./"
```

- Then, run the remaining cells to generate the final submission file.

4 Discussion & Possible Future Work

The approach detailed in this write-up demonstrates several key insights. First, incorporating task-specific priors—such as the known number of rows in the output grid and set a default background pixel value—can lead to substantial improvements over naive baselines. Second, simple and interpretable heuristics, when well-crafted, can outperform unstructured deep learning models that lack domain-specific guidance. Finally, leveraging LLMs through carefully designed few-shot prompts proves to be a competitive strategy, often yielding results on par with more traditional algorithmic and non ML-based approaches.

Despite limitations like compute budget, prompt length, and model constraints, the performance achieved with little tuning seems to confirm the power of careful problem design and domain awareness. Further experiments are required to fully validate these results.

If resources (time and compute availability) allow, I aim to:

- Explore multimodal architectures combining vision and LLM reasoning
- Train symbolic rule extractors from grid pairs to aid LLM planning
- Extend to the full ARC dataset and tackle the official ARC Prize benchmark
- Build a toolformer-style solver where the LLM can invoke utility functions for shape inference or color analysis mid-prompt

5 Acknowledgments

This project was developed in close collaboration with GPT-4o as a coding assistant. Its contributions included brainstorming experimental directions, assisting with iterative code completion and refactoring, and supporting the development of grid evaluation routines, prompt engineering, and strategy testing. The interactive workflow allowed for rapid prototyping and refinement, significantly accelerating the pace of experimentation, given the short-term setting.

I would like to express my gratitude to the organizers for setting up this challenge, which not only provided a stimulating and well-structured benchmark, but also rekindled my engagement with the Zindi platform after a long break. The competition offered a refreshing opportunity to explore abstract reasoning tasks in a focused, time-constrained setting.