Thesis for Bachelor's Degree

# Regulation Using Large Language Models to Generate Synthetic Data for Evaluating Analogical Ability

**Lee, Seungpil (이 승필 李 承泌)**

**School of Electrical Engineering and Computer Science**

**Gwangju Institute of Science and Technology**

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# 대규모 언어 모델을 사용한 합성 데이터 생성 방법에 관한 연구

# Regulation Using Large Language Models to Generate Synthetic Data for Evaluating Analogical Ability

Advisor : Professor Kim, Sundong

by

Lee, Seungpil

School of Electrical Engineering and Computer Science
Gwangju Institute of Science and Technology

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Approved by

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Professor Kim, Sundong

Committee Chair

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Lee, Seungpil

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Committee Chair _____
Prof. Sundong Kim

Committee Member _____
Prof. Mansu Kim

BS/EC
20185132

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## Abstract

As the reasoning abilities of artificial intelligence gain more attention, generating reliable benchmarks to evaluate reasoning capabilities is becoming increasingly significant. Abstract and Reasoning Corpus (ARC) is one of the introduced reasoning benchmarks, providing challenging problems that artificial intelligence has yet to solve. While ARC has been recognized for assessing reasoning abilities, its evaluation format has presented challenges for analysis, leading to the necessity for revised benchmarks. Considering this, our research aimed to modify the benchmark into a multiple-choice language format to make it more suitable for evaluating large language models (LLMs), termed MC-LARC. We evaluated the analogical reasoning abilities of ChatGPT4V with MC-LARC, confirming that 1) a multiple-choice format can support the language model's reasoning capabilities and 2) facilitate evidence analysis. However, we noticed LLMs relying on shortcuts when tackling MC-LARC. By analyzing this, we identified areas to consider in multiple-choice synthesis and specified criteria for what constitutes good choices based on these findings.

# Contents

# Chapter 1. Introduction

Research on artificial intelligence with reasoning capabilities is attracting attention, leading to the proposal of benchmarks to measure such abilities. The Abstraction and Reasoning Corpus (ARC) is one such benchmark designed to evaluate reasoning abilities. Each ARC task consists of 2–5 examples where both input and output are provided, along with one problem where only the input is given. The goal is to infer the rule from the examples and deduce the answer to the problem. The input and output grids in ARC can range from a minimum $1 \times 1$ grid to a maximum $30 \times 30$ grid, with each grid filled with up to 10 different colors. Unlike existing reasoning benchmarks, ARC is specialized in evaluating reasoning abilities alone by reducing the amount of prior knowledge and data required to solve the problems. In this way, ARC is designed to effectively assess inferential abilities; however, its evaluative format, which includes generation, poses challenges in gauging the level of inferential ability achieved. Even if the problem-solving logical process was correct, any deviation in the generated grid leads to the entire response being deemed incorrect. Therefore, evaluating the accuracy of the problem-solving logical process becomes difficult. This challenge is also evident in derived datasets like Mini-ARC [1] and 1D-ARC [2]. These datasets underwent transformations such as fixed grid sizes or reducing 2D arrays to 1D arrays respectively, but they still share the same limitation in that the evaluative format involves generation.

To address this limitation, this paper proposes a modified benchmark called MC-LARC that transforms the evaluation format from generation to selection. It converts the dataset into a multiple-choice language format by using Large Language Models (LLMs) to generate four alternative options based on the correct answer to ARC tasks. We conducted experiments to investigate the impact of the transformation into multiple-choice form and found the following two points: 1) we confirmed an increase in the accuracy of LLMs on ARC problems from about 10% to 75%. This indicates that the options in MC-LARC have served a supportive role in the inference of LLMs, which are more aligned with language generation and comprehension than image processing. 2) Evaluating the extent of the inferential abilities of LLMs becomes more clearly feasible. However, it was observed that LLMs used shortcuts while solving MC-LARC, finding the correct answer by considering the form or internal context of the choices to eliminate inappropriate options, rather than utilizing reasoning abilities. Based on this analysis, it was confirmed that when synthesizing data into a multiple-choice format using LLMs, sufficient and accurate context information should be provided to avoid unnecessary additional information. Additionally, this analysis established criteria for what constitutes good multiple-choice options.

# Chapter 2. Related Works

## 2.1 Benchmark for Analogy Abstraction Tasks

**Abstraction and Reasoning Corpus (ARC)** The Abstraction and Reasoning Corpus (ARC) benchmark [3] was created for the purpose of measuring intelligence in computer systems. This benchmark requires inference based on complex prior knowledge such as arithmetic abilities, geometric understanding, and topological understanding. The goal is to derive common rules from examples and apply them to infer the appropriate output image for a given test input image. Each task provides 2–5 pairs of example input and output images. The original ARC benchmark consists of 400 training set, 400 evaluation set, and 200 test set. Moreover, the ARC benchmark is represented as 2D matrices.

**Language-complete ARC (LARC)** The LARC [4] dataset consists of 400 ARC training data, each accompanied by 1) a description of the input image and 2) a natural language description of the rules between the input and output images. Both the input description and the output description must be language-complete. Language-complete refers to having sufficient relevant information even when neither input nor output images are provided. In other words, humans should be able to understand the task sufficiently based solely on the description of LARC without the presence of images. A language-complete LARC is manifested in the Refined LARC below Figure 3.1.

## 2.2 Synthetic Data Creation Using LLM

Current trends in synthetic data creation with LLMs focus on enhancing the faithfulness and utility of generated data to better align with real-world data distributions. [5] employed grounding, filtering, and taxonomy-based generation techniques to improve the faithfulness of synthetic data for sarcasm detection, which is relevant to our work on MC-LARC's benchmark for assessing LLM reasoning abilities. [6] created synthetic data for evidence-based QA by generating questions and sources, and applying quality filters to distinguish relevant from irrelevant questions. Challenges in generating faithful data have led to proposed filtering techniques to address distribution deviations and improve quality. [7] highlights the importance of avoiding shortcuts in analyzing correct answers, urging us to conduct further experiments to detect flaws and improve methodologies.

# Chapter 3. Methodology

We created MC-LARC through the following two steps: 1) manually refining the existing LARC, and 2) utilizing ChatGPT4 to generate wrong options based on LARC.

**Refining process** The original LARC exhibited significant quality issues, as evidenced by Figure 3.1. These issues manifested primarily in 1) inconsistencies across expressions for the same concept and 2) a lack of information in the provided explanations. For instance, the upper part of Figure 3.1 illustrates different representations for the same concepts, leading to user confusion. Additionally, the explanations accompanying the tasks often omitted crucial information necessary for their successful completion. These issues emerged as a consequence of the dataset's compilation by numerous non-experts using Amazon Mechanical Turk.

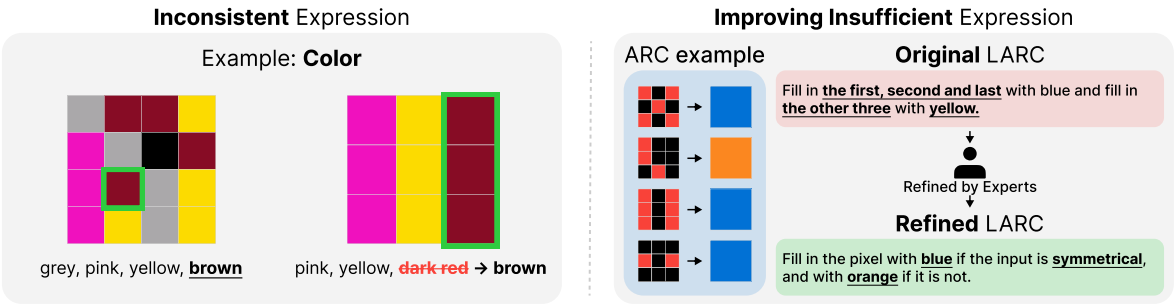


Figure 3.1: Two main issues of LARC. (Left part) There are instances where different expressions are used for the same concept within LARC. For example, some LARC expressions describe brown as "dark red". (Right part) This task involves identifying the symmetry of the input grid to predict the output image result. However, some original LARC expressions provide insufficient information necessary for ARC problem-solving. These have been revised to contain sufficient and accurate information by experts.

In addition to the issues highlighted in Figure 3.1, there were further cases of inconsistency throughout the dataset. These inconsistencies involved not only color but also shape representations and grid manipulation operations. The presence of these multiple issues complicates the process of generating new datasets based on LARC, emphasizing the challenges of relying on flawed data sources.

To address these issues, we conducted a refining process to enhance quality. This process prioritized ensuring consistency in expressions and rectifying erroneous representations. Figure 3.1 provides an overview of this refining process.

**Generating wrong options with ChatGPT4** Based on the given output description of LARC, we generated four distractors through ChatGPT4, as illustrated in Figure 3.2. However, allowing unrestricted generation of distractors led to issues such as creating out-of-context choices unrelated to the task. To address this problem, we improved by adding constraints during the prompt level. The constraints added to the prompt are as follows:

- **In context vocabulary**: To generate plausible distractors, it was necessary to limit the expressions within the context that aligns with the ARC domain. To achieve this, two contextual

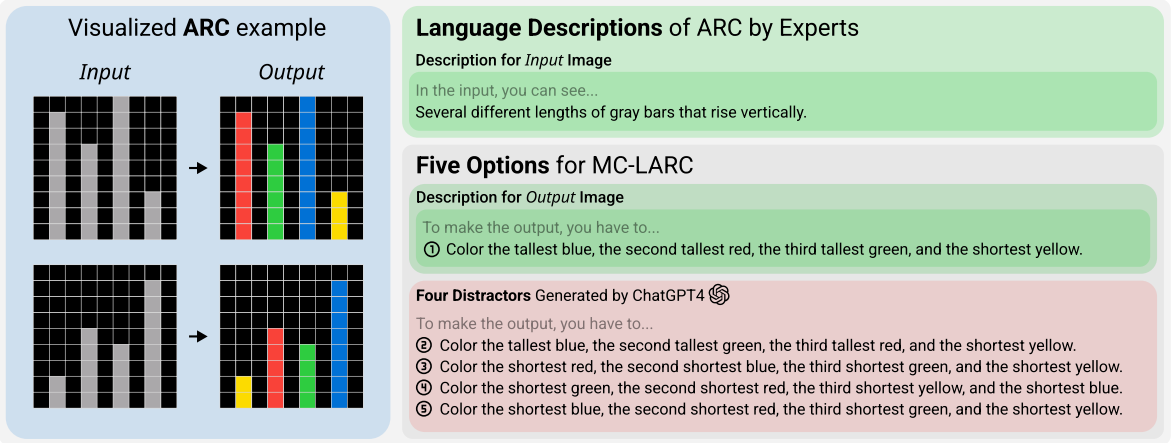


Figure 3.2: The composition of MC-LARC. It consists of a visualized ARC example and five multiple-choice options. The five multiple-choice options consist of the correct solution and four distractors. (Blue part) It visualizes ARC represented as a 2D matrix. (Green part) It is LARC refined manually by experts. (Red part) Using ChatGPT4, four distractors were generated from the output description (Red boundary) of the refined LARC. To solve MC-LARC, the solver must identify common rules from the Visualized ARC example and choose the option that best describes those rules.

constraints were imposed. One involved adding descriptions about the ARC environment, while the other entailed mentioning specific words that should not be used.

- **Length of options**: When generating distractors for lengthy options, there were cases where LLM produced relatively short options, leading to easily solvable problems. Therefore, we restricted the LLM to generate incorrect options of similar lengths to the correct options.

- **Format**: When creating distractors, we ensured that the opening phrases of the sentences exactly matched the correct answer option's *'To make the output, you have to...'*. If the opening phrases of the incorrect options vary, it could lead to selecting the correct answer based on the format rather than the meaning of the sentence.

As shown in Figure 4.3, before constraints were added, the model generated options that were either completely irrelevant to the ARC problem context or altered parts that were not core concepts. These were classified as either `bad` or `moderate`. However, after the constraints were applied, the model did not produce any `bad` options, and the options were classified only as `best` or `moderate`. Despite this improvement, the model still faces the challenge of not being able to produce `best` options for all tasks.

# Chapter 4. Experiment and Results

To verify that the augmented multiple-choice options generated by the LLM did not inadvertently reveal more information than intended, we conducted a control test where the LLM was presented with only the options, devoid of any accompanying images. If the options were crafted appropriately and free from informational bias, the LLM's expected accuracy rate would approximate 20%. Additionally, this image-free experiment required the LLM to justify its choice for each option.

## 4.1 Influence of Multiple Choices

Table 4.1: A table summarizing the results of experiments where ChatGPT4V solved MC-LARC five times. It shows statistics on the accuracy and Krippendorff's Alpha score. The statistics show the mean, standard deviation, and 95% confidence interval for the accuracy. Krippendorff's Alpha score evaluates whether ChatGPT4V's responses are reliable across the five repeated experiments.

| Category | Mean (%) | Std. | 95% CI (%) | Alpha |
|---|---|---|---|---|
| With images | 75.81 | 1.11 | 74.93 - 76.70 | 0.8329 |
| Without images | 64.61 | 1.75 | 63.08 - 66.14 | 0.7995 |

For the MC-LARC, we asked the ChatGPT4V model 5 times per problem, and as shown in Table 4.1, the accuracy of correctly answered tasks out of the total 400 tasks was 75%. Considering that the accuracy of LLMs on ARC tasks is around 10% [8], this is certainly a high score. Additionally, Krippendorff's Alpha score of approximately 0.83 confirmed that the LLM was consistently reasoning the answers.

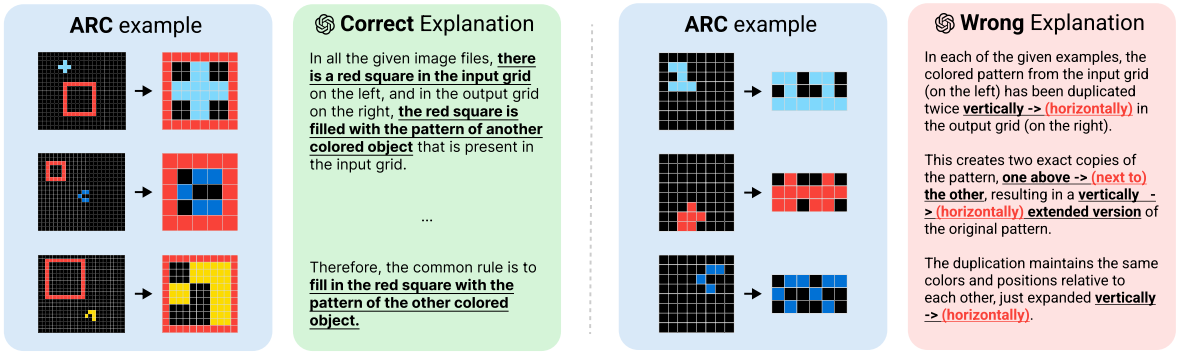


Figure 4.1: A result of requesting an explanation of the experiments with provided images. (Left part) It shows an example where the answer to MC-LARC is correctly chosen. (Right part) It demonstrates the incorrect answers due to failure to infer the correct solution.

To further evaluate the reasoning process of the LLM, we additionally asked for the reason behind selecting each option. As a result, there were cases where both the answer and the reasoning process were correct or both were incorrect, but there were almost no cases where the answer was correct but the explanation was wrong, or where the answer was wrong but the explanation was correct. This indicates a decrease in the errors of generating correct answers through incorrect reasoning processes or

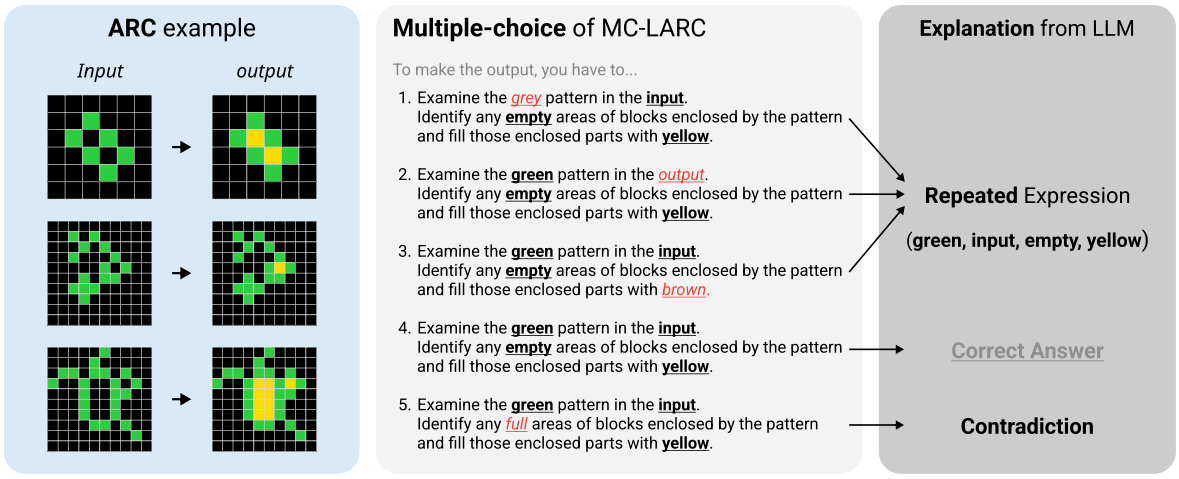


Figure 4.2: Example of an experiment without an image. When given five options, the LLM solves the problem by analyzing them in the following manner. By examining the options, the LLM identifies repeated expressions and excludes the options that use different vocabulary from the others. Additionally, it excludes options that cannot be represented in the ARC grid by identifying semantic contradiction within the sentences themselves.

giving inconsistent answers, which tend to occur when LLMs directly solve ARC tasks [9]. Therefore, even when multiple-choice options, including incorrect options along with the answer description, were provided, we could confirm that the LLM's reasoning ability was partially improved.

## 4.2 Problems on Augmentation

However, there were indications that the LLM found a shortcut when solving MC-LARC. MC-LARC should be solved by inferring the rule from the given images and choosing the correct option, but the LLM achieved an accuracy of 65% even when the task was provided without images. The Krippendorff's Alpha score was also 0.79, not much lower than the experiment with images provided. This can be understood as evidence that the LLM found a consistent logic for getting the correct answers.

To analyze how the LLM solved MC-LARC without the problem images, we additionally asked the LLM to explain the reasoning behind its answers. As shown in Figure 4.2, we found that the LLM inferred the correct option by 1) choosing the option with the most repeated expressions and 2) eliminating options that were self-contradictory.

We point out two problems in the generation process: First, generating four different incorrect options from one correct option became problematic, as the correct option naturally included more repeated words than the incorrect options. Second, not providing image and context information for option generation led to contradictory or incompatible expressions in some options. Therefore, from this experiment, we can conclude that to fairly evaluate reasoning ability, the process of generating choices should be improved to avoid providing additional information that could serve as a shortcut.

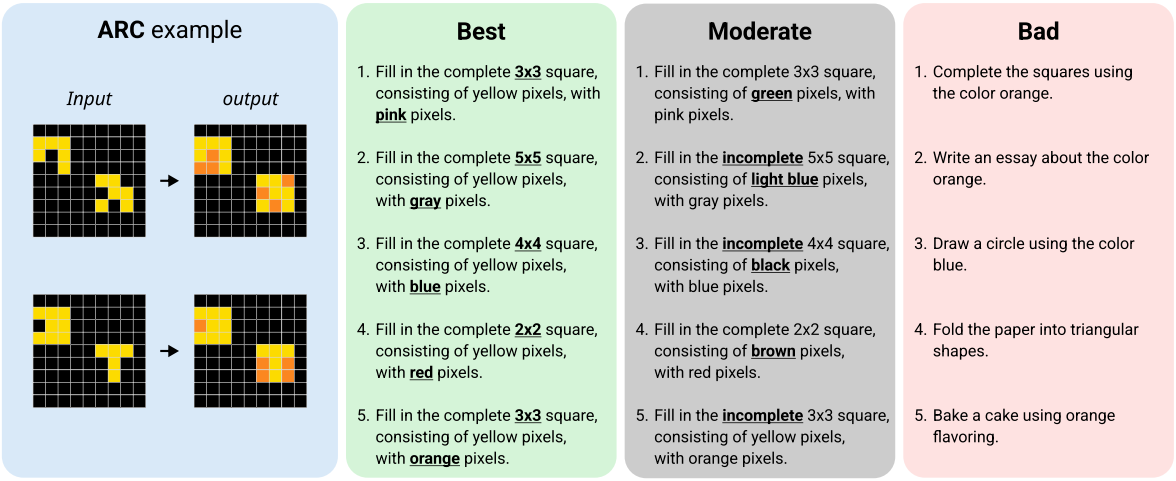


Figure 4.3: Three examples of multi-choice options augmented differently by the LLM. The given problem is to fill in an object with holes with the color orange to make a $3 \times 3$ square, where the size of the square and the color are the core aspects of the problem. The good example demonstrates an understanding of the core of the problem and provides consistent variations, while the poorer examples increasingly include choices that are unrelated to the problem and inconsistent.

## 4.3 Good Option and Bad Option

From the two experiments above, we confirmed that converting to a multiple-choice format has advantages as an inference problem in two aspects: 1) providing additional information to solve the reasoning problem, and 2) allowing for a more transparent evaluation of the reasoning process. However, we also found cases where unintended shortcuts were discovered, and to address this issue, the process of augmenting choices needs to be improved. But before improving the choice generation process, this question must be answered first: What distinguishes a good choice from a bad choice?

As we examined the augmented choice examples generated by the LLM, we were able to categorize the choices into three levels of quality, as shown in Figure 4.3. The best choices modified the core part of the problem that fits the context. In ARC, the core is the part where a change occurs between images, so in the given examples, completing a square by filling in orange pixels is the core. Thus, choices questioning the change to orange can be considered the best type of choice. Next, choices that were possible to predict from the input image but did not capture the core of the problem were of moderate quality. Examples include using colors not present in the input image or specifying grid sizes that were not present. Finally, choices that included cases that cannot occur in the ARC domain at all were the worst. Commands like "Write an essay" are irrelevant to ARC and do not require any reasoning process to solve the problem, making them poor choices. Therefore, good text descriptions and choices should 1) include the core of the problem in the choices, and 2) be consistent within the context of the problem. Identifying the criteria in form and content needed to generate good choices during the augmentation process is the contribution of this study.

# Chapter 5. Conclusions

In conclusion, to overcome the limitations of the existing ARC in measuring inferential reasoning ability, we created a new multiple-choice dataset called MC-LARC. As a result, the multiple-choice format allowed for a clearer analysis of logical flow during problem-solving and provided supplementary support for the solver's reasoning abilities. However, in an additional control experiment without images, we found that the LLM solved problems by finding shortcuts instead of using reasoning abilities. This highlights the regulation needed when using LLMs to synthesize multiple-choice questions. Based on these findings, we propose specific conditions for designing multiple-choice questions that effectively evaluate the required reasoning abilities without enabling shortcuts.

These findings have several important implications. Firstly, they offer valuable insights into the appropriate methods for evaluating inferential reasoning, demonstrating the potential of using multiple-choice questions for this purpose. Secondly, by identifying the constraints to consider when using LLMs to synthesize multiple-choice questions, this research paves the way for the development of more sophisticated and automated high-quality question generators.

# Summary

## Regulation Using Large Language Models to Generate Synthetic Data for Evaluating Analogical Ability

인공지능의 추론 능력에 대한 관심이 높아짐에 따라, 추론 능력을 평가하기 위한 신뢰할 수 있는 벤치마크를 생성하는 것이 점점 더 중요해지고 있다. Abstract and Reasoning Corpus(ARC)는 인공지능이 아직 해결하지 못한 도전적인 문제를 제공하는 추론 벤치마크 중 하나이다. ARC는 추론 능력 평가에 있어 인정받고 있지만, 그 형식은 분석에 어려움을 제시하여 개선할 필요를 보였다. 이를 고려하여, 본 연구는 대규모 언어 모델(Large Language Models, LLMs)을 평가하기에 적합하도록 다중 선택 문제의 형식으로 수정한 MC-LARC 벤치마크를 만들고 LLM에게 적용해보는 것을 목표로 한다. MC-LARC를 통해 ChatGPT4V의 유추 추론 능력을 평가해본 결과 다중 선택 형식이 언어 모델의 추론 능력을 지원할 수 있으며, LLM의 추론 과정에 대한 분석을 용이하게 한다는 것을 확인하였다. 그러나 한편 LLM이 MC-LARC를 해결할 때 가장 빈번하게 사용된 단어를 추적하거나 모순된 선지를 소거하는 등 몇 가지 편법을 찾아내는 것도 확인하였다. 이를 분석함으로써, 다중 선택 합성에서 고려해야 할 영역을 식별하고 이러한 결과를 바탕으로 좋은 선택지가 되기 위한 기준을 명시하는 것 까지가 본 연구의 기여이다.

# 감 사 의 글

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# 약 력

이 름: 이승필
생 년 월 일: 2000년 01월 15일
출 생 지: 대전
주 소: 경기도 과천시 과천대로 8길 15

## 학 력

2016. 3. – 2018. 2. 배재고등학교
2018. 2. – 2024. 8. 광주과학기술원 전기전자컴퓨터공학부 (학사)

## 경 력

2020. 6. – 2021. 1. 광주과학기술원 BioComputing Lab 연구 인턴
2022. 1. – 2023. 9. 대한민국 해군 소프트웨어 개발팀
2023. 9. – 2024. 6. 광주과학기술원 DataScience Lab 연구 인턴

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