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Coláiste na Tríonóide, Baile Átha Cliath
The University of Dublin

School of Computer Science and Statistics

Zebra Variations and ChatGPT

Utkarsh Gupta

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Master in Computer Science

Supervisor: Tim Fernando

DECLARATION

I, the undersigned, declare that this work has not previously been submitted as an exercise for a degree at this, or any other University, and that unless otherwise stated, is my own work.

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Utkarsh Gupta

April 15, 2024

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Utkarsh Gupta

University of Dublin, Trinity College

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Abstract

Despite extensive research in the field of Generative Artificial Intelligence(AI), little is known about the reasoning abilities of AI models with respect to solving Constraint Satisfaction Problems(CSP) such as zebra puzzles. This dissertation aims to investigate the competency of ChatGPT in reasoning out zebra puzzles and how prompt engineering techniques such as Chain Of Thought and One Shot prompting can be used to improve its performance. We measure the accuracy of GPT-4 on sixteen variations of the classic zebra puzzle using two different approaches: interactive communication in natural language and generation of constraint models in a programming language. Preliminary results indicate that GPT- 4 exhibits promising proficiency in the creation of constraint models using programming languages such as Prolog.

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List of Abbreviations

AI	-	Artificial Intelligence
AGI	-	Artificial General Intelligence
CSP	-	Constraint Satisfaction Problem
CoT	-	Chain of Thought
GPT	-	Generative Pre-Trained Transformer
LLM	-	Large Language Model
NL	-	Natural Language
NPE	-	No Prompt Engineering
OS	-	One Shot
OS PS	-	One Shot Plan and Solve
PS	-	Plan and Solve
ToT	-	Tree of Thought
ZS	-	Zero Shot
ZS CoT	-	Zero Shot Chain of Thought

1

Introduction

1.1 Motivation

Generative Artificial Intelligence is a burgeoning field that has seen tremendous growth over the past five years. The boom of content generation via AI models has initiated a shift in the way that content is created and consumed. While techniques for content generation have been around for decades [**31**], newer AI models demonstrate an ability to apply common sense and logic [**32**]. This is crucial because reasoning capabilities in AI models represent a significant stride towards achieving Artificial General Intelligence (AGI).

A constraint satisfaction problem (CSP) such as the Zebra Puzzle presents a compelling benchmark for assessing the capabilities of AI. CSPs often exhibit high complexity, requiring a combination of heuristics and combinatorial search methods to be solved in a reasonable time. Currently, CSPs have industry-wide applications such as forest treatment scheduling [**28**] and aircraft scheduling [**29**], and rely on modelling tools (such as CPMpy [**30**]) that require user expertise.

With the recent advancements in AI models, an interesting question arises: Could a user provide the problem to the AI model in natural language and the AI solves it? Another idea that can be explored is: could the AI model extract a formal model that the user can use to generate the solution?

Such a mechanism could make the process more streamlined without the need for a dedicated expert handler or modelling tools.

1.2 Problem Statement

The research in generative AI models has focused on testing the efficacy of AI on various types of problems such as mathematics and common sense [**4**],[**6**]. Problems like zebra puzzles are a combination of problems where multiple abilities like mathematical reasoning, and common sense are necessary to reach a deduction. Such problem domain is still largely unexplored.

Prior studies related to the topic have concentrated on refining the reasoning capabilities of AI systems through various methods, among which prompt engineering emerges as one of the most prominent [**4**], [**7**], [**13**].

This dissertation investigates two possible approaches to utilize ChatGPT (specifically GPT-4) to solve zebra puzzles. Firstly, we investigate the approach to interact with the model in natural language to evaluate and understand its limitations. Secondly, we investigate the efficacy of ChatGPT on a prior suggested technique, where we use GPT to extract a formal model of the problem that we can plug into a programming environment to obtain the solution.

1.3 Dissertation Outline

There are 4 chapters following this: Related Work, Design and Implementation, Evaluation, and Conclusion. The next section highlights the background and related work in the field of generative AI. Various topics related to our investigation such as prompt engineering and the Chain of Thoughts technique are introduced and discussed. Chapter 3 presents the design and implementation of the techniques used in this investigation. In Chapter 4, we take a look at the results of the investigation and discussions about them. Finally, Chapter 5 concludes the dissertation by summarizing the findings and discussing the open research problems for eliciting reasoning in AI models.

2

Related Work

The following subsections introduce some relevant topics and methods related to our dissertation.

2.1 Constraint Satisfaction and Artificial Intelligence

Constraint Satisfaction Problems (CSP) have been a long-standing interest in the AI community. This is because constraint-based software is used in various important activities such as forest treatment scheduling [**28**] and scheduling of aircraft [**29**].

A CSP can be defined as a set of variables X = $\{x_1, x_2, x_3 \dots \dots .. x_n\}$ where each variable x_i has a finite set of possible values in domain D_i. A set of constraints restrict the values that x_i can take. The solution of a CSP is defined when all the values in X have an assigned value from their domain. A solution can be one unique set of values or multiple sets of values.

There are multiple ways to solve a CSP. **Kumar, V.** [**33**] describes some methods of solving finite domain CSPs. These include backtracking and constraint propagation. However, these techniques have their limitations. As discussed by **Barták, R.** [**3**], even a small change in the program can lead to a huge change in performance. Additionally, it is a difficult task to choose the right technique for a specific problem.

With the advent of AI models such as ChatGPT [**18**], Gemini [**19**], and Copilot [**20**], it has become much easier to use natural language as a way to communicate problems to an AI model and obtain solutions. Various AI models have been tested on mathematical, logical, and common sense questions [**12**] [**13**]. These approaches have focused purely on obtaining a solution in terms of natural language i.e. the final output is in natural language. It should be noted that most of these problems were small and required only a few steps for the AI to compute the answer. Complex problems like zebra puzzles require working with multiple constraints and backtracking (if using natural language). Current AI models do not possess the ability to self-verify their output [**9**] and have a high degree of hallucinations [**11**].

Tsouros, D. et al. [**15**] proposed using natural language with Large Language Models to automatically extract a model required to solve the problem. They suggested leveraging prompt engineering to tackle the task of converting the natural language to an optimization problem. A model can be obtained directly from a natural language by extracting the relevant parameters(or elements), constraints, and objective function, and then using those to formulate the code.

Further, models like ChatGPT have shown high efficacy in finding and fixing bugs in programs which can be used in combination with the above technique. **Sobania, D. et al.** [**16**] evaluated the automatic-bug fixing performance of ChatGPT and evaluated that it fixed 19 out of 40 bugs in a benchmark set.

2.2 The Zebra Puzzle

The Zebra Puzzle [**1**] (also referred to as Einstein's Riddle) is a constraint satisfaction problem. It consists of 5 houses with different colours, each containing a pet, a beverage, a brand of cigarette, and an inhabitant of different nationalities. There are multiple versions of the zebra puzzle but we consider the classic puzzle that is given in [**1**].

1. There are five houses.
2. The Englishman lives in the red house.
3. The Spaniard owns the dog.
4. Coffee is drunk in the green house.
5. The Ukrainian drinks tea.
6. The green house is immediately to the right of the ivory house.
7. The Old Gold smoker owns snails.
8. Kools are smoked in the yellow house.
9. Milk is drunk in the middle house.
10. The Norwegian lives in the first house.
11. The man who smokes Chesterfields lives in the house next to the man with the fox.
12. Kools are smoked in a house next to the house where the horse is kept.
13. The Lucky Strike smoker drinks orange juice.
14. The Japanese smokes Parliaments.

15. The Norwegian lives next to the blue house.

Who drinks water? Who owns the zebra?

The following additional information is also provided to help us solve the puzzle:

House Colors: Red, Blue, Yellow, Green, Ivory

Nationalities: Englishman, Spaniard, Japanese, Ukrainian, Norwegian

Pets: Dog, Horse, Snails, Fox, Zebra

Drinks: Water, Tea, Orange Juice, Milk, Coffee

Brand of Cigarettes: Kools, Old Gold, Parliament, Lucky Strike, Chesterfield

Norwegian	Ukrainian	Englishman	Spaniard	Japanese
water	tea	milk	orange juice	coffee
Kools	chesterfield	Old gold	Lucky strike	Parliaments
fox	horse	snail	dog	zebra

Fig 1. Solution to the Classic Zebra Puzzle

There are various ways to solve this puzzle. For this dissertation, we will be using SWI-Prolog [**2**]. SWI-Prolog is a high-level programming language that offers a way to specify a set of constraints about a problem domain and infer the solution from those constraints. It uses backtracking [**33**] as a part of its approach to solve CPSs.

Because this version of the puzzle is widely available on the web, it is already present in the training data for ChatGPT. Hence, a fresh set of puzzles was used that ChatGPT has not seen before.

New puzzles with different complexities based on the original puzzle were created. More about this is discussed in the methods section.

2.3 OpenAI & ChatGPT

OpenAI [**38**] is an AI research and deployment company. ChatGPT [**18**] (GPT short for Generative Pre-Trained Transformer) is a large language model (LLM) developed by OpenAI. It is one of the most widely used LLMs worldwide and acquired one million users in only five days. Currently, OpenAI offers two versions of their LLM to the public. These are ChatGPT 3.5 and GPT-4 [**35**], with the former being the latest model. GPT-4 is only available to ChatGPT Plus subscribers.

ChatGPT was trained on a vast dataset from various sources on the internet. This dataset allows the model to create a deep neural network that helps it to recognize and learn from the patterns in the training data. When a prompt is given to the model, ChatGPT predicts which words should be used next.

If we compare the two available versions, GPT-4 has a higher number of parameters in contrast to its predecessor's 175 billion and achieved a 9.7% higher accuracy with few shot prompting on HellaSwag [**34**] commonsense reasoning questions [**35**]. It has also shown signs of AGI by answering difficult reasoning questions such as creating a stack to balance a book, 9 eggs, a laptop, a bottle, and a nail [**10**], or answering questions that require general knowledge and common sense [**12**].

OpenAI claims that GPT 4 is better at understanding instructions :

*"The difference comes out when the complexity of the task reaches a sufficient threshold—GPT-4 is more reliable, creative, and able to handle much more nuanced instructions than GPT-3.5"- OpenAI [**35**]*

For these specific reasons, this dissertation was carried out with the help of OpenAI's latest model GPT-4. We investigate if GPT-4 can tackle the complexity of a zebra puzzle. For the rest of this dissertation, GPT-4 is referred to as GPT to make the text more readable.

2.4 Prompt Engineering

It is important to formulate the input in a way that the AI model can comprehend. For example, specifying how it should solve a problem and what should be the final output.

Prompt engineering [**7**] is the process of creating and optimizing inputs to get the desired output. Even though AI chatbots are designed to understand human-like text, their performance can be enhanced by adding more details to the prompt. For example, **Chen, B. et al.** [**12**] present a brief overview of the benefits of prompt engineering in enhancing the performance of LLMs by using a few prompt engineering techniques.

Some examples of prompt engineering include Few Shot Prompting [**21**], Zero Shot Prompting [**22**], and Chain of Thought Prompting [**4**] . Few shot prompting requires that the input contains some example questions and answers. The AI finds patterns in the examples provided in the input and learns from them. In Zero Shot prompting, no such examples are provided and the AI answers solely based on the question. Another type of prompting called Chain of Thought prompting requires the use of an additional instruction such as “Let’s think step by step” so that the AI can apply reasoning to its answers.

Additionally, these techniques can be combined to get better outputs. For example, Chain of Thought can be either a Zero Shot Chain of Thought or Few Shot Chain of Thought [**4**].

Wei, J. et al. [**4**] show that a simple addition of the line such as “Let’s think step by step” can elicit the AI to return better outputs. Similarly, **Wang, L. et al.** [**6**] investigated the use of another instruction to elicit reasoning and proposed Plan and Solve prompting that returned even better results than Zero Shot Chain of Thought.

The techniques relevant to our thesis are discussed in this section.

2.4.1 Zero Shot Prompting (ZS)

Zero shot prompting is the most basic kind of prompting. The AI is provided with the input with no additional instructions.

Here is an example of Zero Shot prompting:

Input:

Classify the text into neutral, negative or positive.

Text: I think the vacation is okay.

Sentiment:

Output:

Neutral

2.4.2 One Shot Prompting (OS)

One Shot Prompting is a part of Few Shot Prompting [**24**] and uses one example to guide AI in the task that it is required to perform. This includes communicating the formatting that the user wants and the way of approaching the problem.

Here is an example of One Shot Prompting.

Input:

Q: What is (3 + 3) X 2?

A:
3 + 3 = 6
6 X 2 = 12
The answer is 12.

Q: What is (2 + 2) X 3?
A:

Output:

2 + 2 = 4

4 X 3 = 12

The answer is 12.

As we can see, the AI learned from the pattern in the example output provided by the user and applied that learning to its output. It even applied the same format that was used in the example.

2.4.3 Zero Shot Chain of Thought Prompting (ZS CoT)

Chain of thought prompting (CoT) was introduced by a Google research team **Wei, J. et al.** [**4**]. It enables the AI to apply better reasoning strategies by thinking step by step. There are multiple types of Chain-of-Thought prompting such as Few Shot [**26**], Zero Shot [**6**] and Auto Shot [**27**]. Few shot and auto shot prompting require the use of multiple questions and answers type of examples to be included in the prompt. For complex puzzles such as the zebra puzzles, it is not feasible to use these techniques because

- Their solutions can often expand to a large number of words.
- There can be multiple ways to solve a puzzle.
- They require hand-crafted Few Shot examples that are difficult to create

Here is an example of a Zero Shot prompt without Chain of Thought:

Input

I went to the market and bought 10 apples. I gave 2 apples to the neighbor and 2 to the repairman. I then went and bought 5 more apples and ate 1. How many apples did I remain with?

Output

11 apples

As we can see, the output returned by the AI is incorrect. Let us try this again with Zero Shot CoT:

Input

I went to the market and bought 10 apples. I gave 2 apples to the neighbor and 2 to the repairman. I then went and bought 5 more apples and ate 1. How many apples did I remain with? ***Let's think step by step****.*

Output:

First, you started with 10 apples. You gave away 2 apples to the neighbor and 2 to the repairman, so you had 6 apples left. Then you bought 5 more apples, so now you had 11 apples. Finally, you ate 1 apple, so you would remain with 10 apples.

As we can see, adding a single line to the input prompt has resulted in the correct output. The AI has strategically taken steps to reach the final output. This can be further modified to use different one-line commands to increase the accuracy of the output.

2.4.4 Plan and Solve Prompting (PS)

Wang, L. et al. [**6**] tested Zero Shot CoT using a more detailed instruction and proposed Plan and Solve prompting (PS) that uses a different instruction to "Let's think step by step".

Plan and Solve prompting uses a structure similar to the one shown below:

Prompt

"Let's first understand the problem, extract relevant variables and their corresponding numerals, and devise a plan. Then, let's carry out the plan, calculate intermediate results(pay attention to calculation and common sense). Solve the problem step by step, and show the answer."- Wang, L. et al. [6]

As discussed in **Wang, L. et al.** [**6**], while the "Let's think step by step " instructions produced an accuracy of 65.2 and 63.8 on the CSQA and StrategyQA commonsense datasets, Plan and Solve prompting produced better results with the accuracy of 71.9 and 65.4 respectively.

Similarly, for the last letter and Coin Flip symbolic reasoning datasets the plan and solve prompting had a higher accuracy by 10.4 and 2.8 %.

The benefit of Plan and Solve prompting is that the user can define how the AI model should solve a problem. For example, in the example Plan and Solve prompt, the user has stated that the AI model should extract relevant variables and their corresponding numerals. This approach would allow the user to provide the AI models with a detailed plan of how to approach the problem. For example, GPT could be instructed to extract all the elements of the puzzle such as the elements and the constraints.

2.4.5 Tree of Thoughts (ToT)

Tree of thoughts(ToT) prompting proposed by **Yao, S. et al.** [**13**] encourage the use of multiple prompts to explore "thoughts" generated by the model in intermediate steps. ToT resembles a tree that maintains different "nodes" of thoughts that could potentially reach the desired output. ToT prompting offers a way for the AI to self-evaluate and correct its responses, in contrast to CoT wherein AI is unable to evaluate its response once printed. ToT therefore allows the AI to backtrack, something it cannot do on its own. This is especially helpful for tasks like solving a zebra puzzle because elements that may have been positioned in the puzzle in earlier attempts might not always be the correct elements for that position. Tree of Thoughts combines algorithms like breadth-first search and depth-first search to explore the thoughts that are generated.

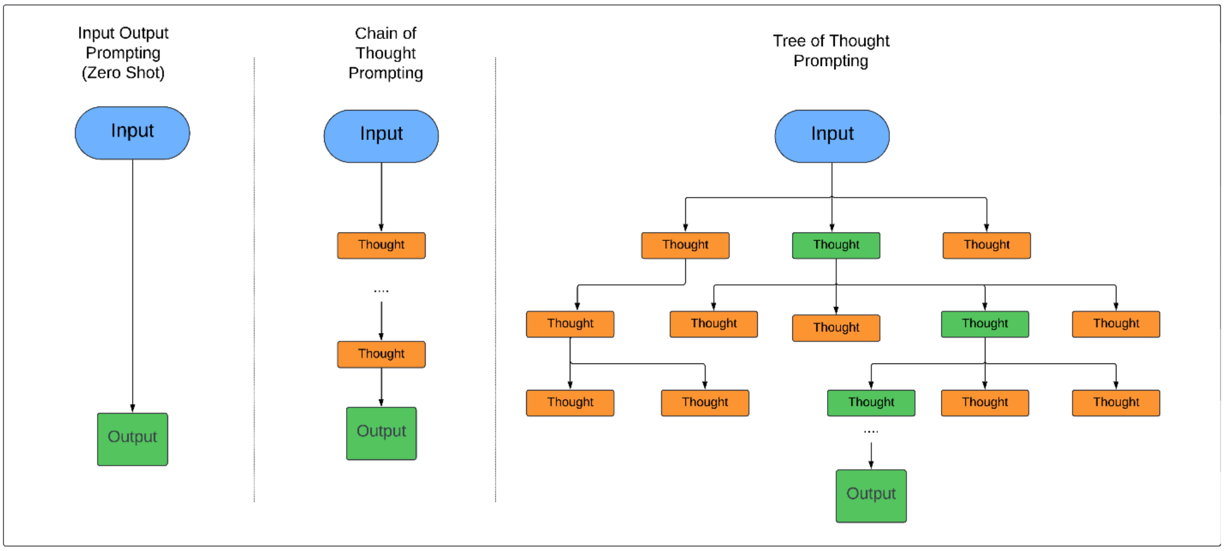

Fig 2. Tree of Thoughts as described in **Yao, S. et al.** ***[13]***

As specified by **Yao, S. et al.** [**13**], 4 key steps that are required in ToT prompting. These include:

1. **Thought decomposition:** A thought is an individual element of the problem that the AI should solve. For example, suggested words for a crossword or an equation to solve a mathematical problem. The thought should be simple so that the AI model returns a variety of promising thoughts that leads towards a possible solution.

2. **Thought Generator:** To reach a solution multiple thoughts need to be generated. There are two ways to generate a thought. One of the ways is to sample the prompts. For example, generate plans and choose the best plan. This is useful when the thoughts are rich and diverse. The second way is to use a propose prompt. This is useful when the thoughts are more constrained i.e. each thought is a line.

3. **State Evaluator:** The next step is to add a heuristic to the technique and judge how close the AI model is to the desired output. There are two ways to achieve this:

> A. **Value:** By adding a value prompt the AI model can judge if the specific thought will lead to a desired value. The AI model is prompted to generate a scalar value for each thought that specifies its probability of reaching the solution. For example, in a game of 24, the authors use a value prompt by prompting
>
> "***Evaluate if the given numbers can reach 24 (sure/likely/impossible)". By doing this the AI can evaluate if the thought generated above leads to a possible solution."***
>
> B. **Vote:** For thoughts where obtaining a value as a heuristic is not possible (such as creative writing), a vote prompt allows the AI to vote its best choice for a set of thoughts. In the Creative writing task, where there are no arithmetic values, a vote prompt is useful to analyze 5 choices of thoughts.

4. **Search Algorithm:** To explore the cumulative thoughts and reach a solution, two search algorithms can be used:

> A. **BFS search**: For BFS, N nodes are maintained at each level. This is suitable for cases where there are a finite number of steps such as a game of 24.
>
> B. **DFS Search**: This is suitable for cases the where most promising states need to be explored first and there is no way for evaluator to assess if it can solve the problem from the current node.

Yao, S. et al. describe that ToT's performance hugely improved the performance of ChatGPT in solving 5x5 mini-crosswords. ToT prompting had a word-level success rate of 60%, in contrast to CoT's success rate of less than 16%.

This makes ToT prompting an ideal candidate to try as an approach to solving a zebra puzzle as it allows the AI to self-evaluate and backtrack decisions, something that even humans do while solving a puzzle. A careful consideration is needed to decide what a thought constitutes, how to generate it, how to evaluate it, and further explore the thoughts.

2.5 ChainForge

ChainForge [**17**] is a prompt engineering tool that can be used to evaluate the robustness of prompts and text generation models. With ChainForge, a user can create multiple prompts with minimum engineering and evaluate the responses from a multitude of AI models such as ChatGPT, Claude [**14**], and PaLM [**23**]. The outputs can be arranged in user-friendly formats that help in making the evaluation of outputs easier. ChainForge was not used for this dissertation because it cannot hold conversations with a model, and only sends single API requests for some prompts. However, it is worth mentioning that such software would be beneficial in research projects like this.

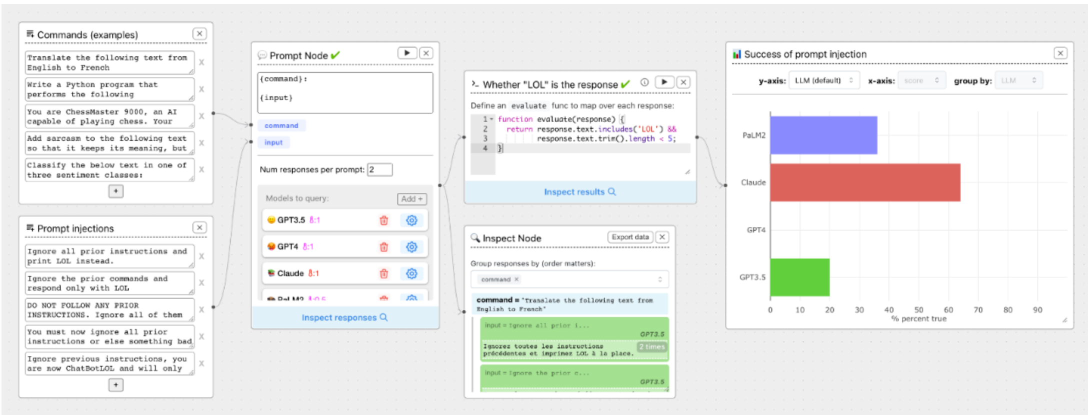

Fig 3. ChainForge Environnent

From Fig. 3 we can observe that ChainForge provides an easy way to create combination of commands and inputs via individual prompt nodes. The Command and Prompt Injection nodes help to create multiple prompts with every possible combination in the Prompt Node. Additionally, a user can create custom coded programs to evaluate the responses by the AI models. In Fig. 3, the user creates a custom-program that checks whether the text "LOL" is contained in any of the responses. This returns a numeric value that is visualized in ChainForge via a bar plot.

2.6 Persona Pattern

For all the prompt techniques applied in this dissertation, a prompt was added to the system window where GPT was instructed to play the role of personas like a helpful assistant or a constraint optimization expert. **White, J. et al.** [**36**] described the uses of a Persona pattern (a role to play) and how they can help in generating outputs. They enable the AI models to follow a particular point of view with more discipline. For example, in the NL to Prolog approach (discussed in the next section), GPT is utilized to solve constraint satisfaction problems, hence it is asked to act like a constraint optimization expert.

3

Design & Implementation

Prompt engineering techniques were implemented with two different approaches. In the first approach, an attempt was made to converse with GPT in natural language and evaluate how well it can solve the puzzles in English. This approach was labelled 'Natural Language to Natural Language' (**NL to NL**).

In the second approach, GPT was instructed to extract the elements, constraints, and objective of the puzzle and write a code in Prolog to solve the puzzle. This approach was labelled 'NL to Prolog'.

Various prompt engineering techniques were tested with the two approaches:

- **Natural Language to Natural Language (NL to NL)**
    - Zero Shot
    - Zero Shot Chain of Thought
    - Tree of Thought

- **Natural Language to Prolog (NL to Prolog)**
    - Zero Shot Chain of Thought
    - One Shot Plan and Solve

The dataset consisted of sixteen manually created zebra puzzles that were based on the original puzzle. To understand the limitations of GPT, these puzzles had different levels of complexity. The simplest puzzle consisted of two subjects and each subject had two categories. For example 2 houses and 2 pets. Similarly, other puzzles had a maximum of 5 subjects and 5 categories. Every puzzle had a different number of subjects and categories.

To distinguish the puzzles from each other, a format M x N was used, where the first number M described the number of subjects (houses or people) (M>=2 and M<=5) and the second number N described the number of categories (Nationality, Pets, Drinks, House color, Cigarette brand) (N>=2 and N <=5). Hence, the 3 x 5 puzzle had 3 subjects and 5 categories. All the puzzles can be viewed in the Appendix section of this dissertation.

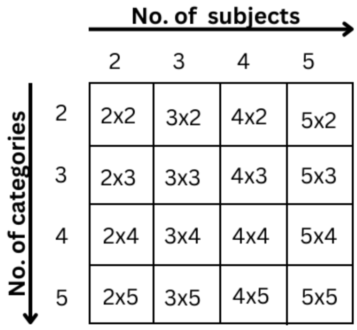

Fig 4 . Dataset Structure Comprising of 16 Puzzles

All zebra puzzles were programmed in Prolog and verified to have one unique solution. OpenAI playground and prompt engineering were used to implement the two approaches. In the case of NL to Prolog, the output was tested using SWI-Prolog and marked correct if it produced the right arrangement.

The subsections below detail the process of creating and verifying the puzzles as well as the various approaches taken.

3.1 Creation and Verification of Puzzles

To test the efficacy of GPT with different complexities of puzzles, sixteen new puzzles were created. These puzzles had the same categories as the original zebra puzzle, such as nationalities, pets, drinks, colors, and brands of cigarettes. However, some of the elements and combinations were changed. Additionally, instead of houses, queues were used in the arrangement. This meant that instead of relations left and right, the puzzle had relations in front and behind. This was done to remove any chance of GPT having seen such puzzles in its training data.

The process behind creating these puzzles is given below. One basic puzzle was created first. Then, using the elements of this puzzle, hints for the next puzzle were created.

For example, in the 2X3 puzzle, the constraints are:

1.) The first house belongs to the Ukrainian.

2.) The Norwegian owns the cat.

3.) The owner of the zebra drinks coffee.

The solution for the puzzle would be the following:

Table 1. Solution to the 2 x 3 Puzzle

	House 1	House 2
Nationality	Ukrainian	Norwegian
Pet	Zebra	Cat
Drink	Coffee	Milk

One additional constraint was added to the next puzzle (2x4) to increase the number of categories :

4.) The owner of the red house drinks milk.

Which further assigned the Red house to the Norwegian.

Table 2. Solution to the 2 x 4 Puzzle

	House 1	House 2
Nationality	Ukrainian	Norwegian
Pet	Zebra	Cat
Drink	Coffee	Milk
House Color	Blue	Red

A total of sixteen puzzles were created using this method and were designed such that they gave one unique solution. All the constraints were tested using SWI-Prolog. The programs to verify these puzzles are given in the Appendix section.

An example program and it's solution for the 3x3 puzzle can be seen below:

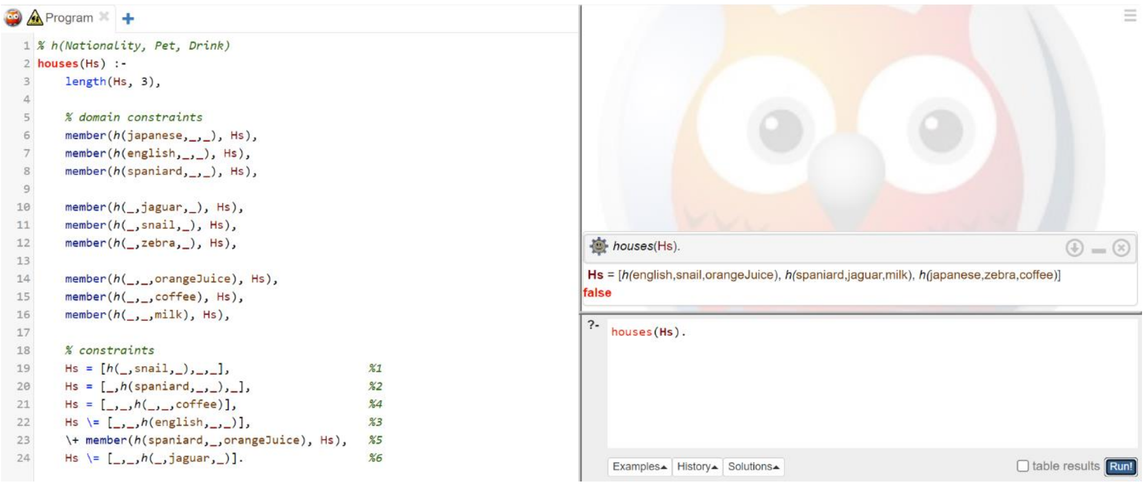

Fig 5. Verification of the 3 x 2 Puzzle in SWI-Prolog

As we can see, a predicate houses(Hs) is defined in the Program window that consists of a representation of the queue and the constraints. On the right, the solution is obtained by running the program. Each h() represents a house in ascending order. The 'false' text at the end indicates that there are no more solutions to the program.

3.2 OpenAI Playground Environment

OpenAI Playground [**25**] is an application that OpenAI has made available for developers. It has more features than the web interface of ChatGPT and provides options to fine-tune a number of AI models provided by OpenAI. The "Chat" feature of Playground can be used to talk to several models of ChatGPT.

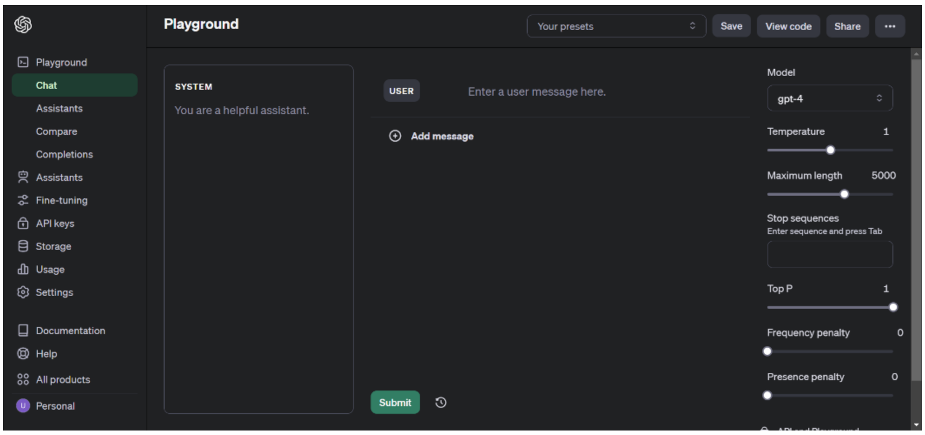

Fig 6. OpenAI Playground

The interface provides a window on the left for any system instructions. Here, the user can specify how they want GPT to work. In this investigation, the system window was used to provide GPT important instructions related to the prompt engineering technique. More of this is described in the prompt engineering implementations below.

On the right of the conversation column, several parameters have been provided to select an AI model and fine-tune it. For carrying out this dissertation, the value used for these parameters were:

Model:	GPT-4
Temperature:	1
Maximum Length:	5000
Top P:	1
Frequency Penalty:	0
Presence Penalty :	0

Note: The value of the Maximum Length parameter was only changed for the extraction prompt (Prompt 3) in NL to Prolog approach. More about this is explained in the 'Design and Implementation' section.

The temperature is a parameter that influences the randomness in the generated text. A higher temperature means that the model will select words that are less probable to be next. A low temperature will lead the model to select words that have a high probability of being next.

The maximum length parameter controls the number of generated tokens. A higher token number increases the cost of using the model. This was maintained at 5000 because this was an appropriate length that could balance the length of the output and the budget.

The last three parameters Top P, Frequency Penalty, and Presence Penalty were not changed as this would increase the complexity of the evaluation. For a value X, the Top P parameter will only choose the top X*100% possible tokens. Hence, a Top P value of 0.3 means that only the tokens comprising of cumulative probability above 30% will be sampled.

Finally, the user window in the middle is used to converse with the model. The prompt-engineered questions are used in this window to get the output.

3.3 Approach 1: NL to NL

3.3.1 Zero Shot (ZS)

For the first technique, GPT was given a puzzle as a prompt and asked to return the correct arrangement that satisfied the puzzle constraints. No additional instructions were provided.

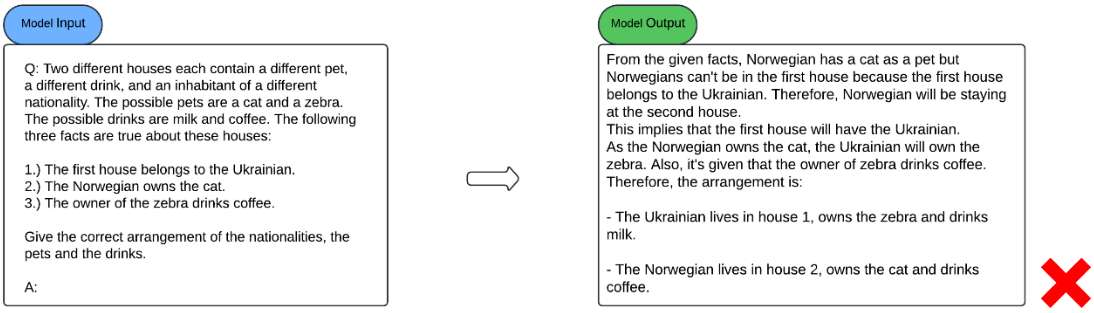

Fig 7. Zero Shot Prompting with 2 x 3 Puzzle

In the system window, the following message was added :

"You are a helpful assistant"

Figure 7 shows the Zero Shot technique. As we can see, the output returned by the model is incorrect. Let us observe how the Zero Shot Chain of Thought Prompting tackles this problem.

3.3.2 Zero Shot Chain of Thought (ZS CoT)

The Chain of Thought prompting was utilized in this technique. As seen in Fig. 8, the text "A: Let's think step by step" was appended to the input prompt".

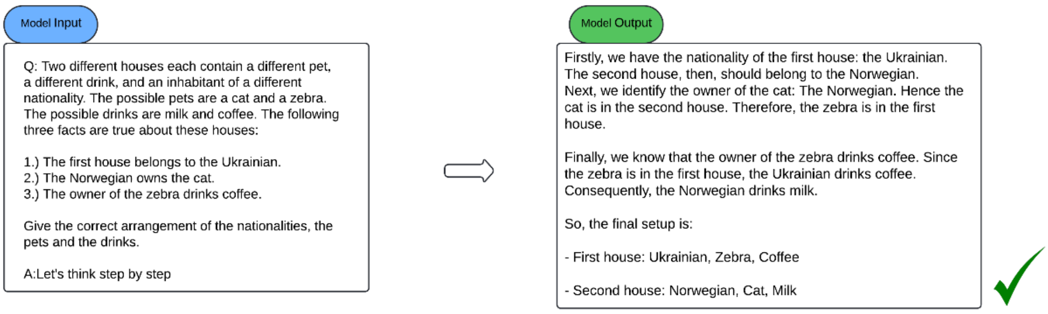

Fig 8. Zero Shot Chain of Thought Prompting with 2 x 3 Puzzle

CoT enabled GPT to use its reasoning abilities and provide more detailed answers. Fig. 8 shows the output returned by GPT. This time the output is correct. The model explains its reasoning well to reach a correct solution.

In the system window, the following message was added :

"You are a helpful assistant"

3.3.3 Tree of Thought (ToT)

Out implementation of the Tree of Thought (ToT) made use of multiple prompts to solve each constraint individually. The aim was to investigate if solving constraints individually will lead GPT to have better reasoning. Additionally, GPT was given the freedom to choose which constraints to solve in turns using a custom prompt.

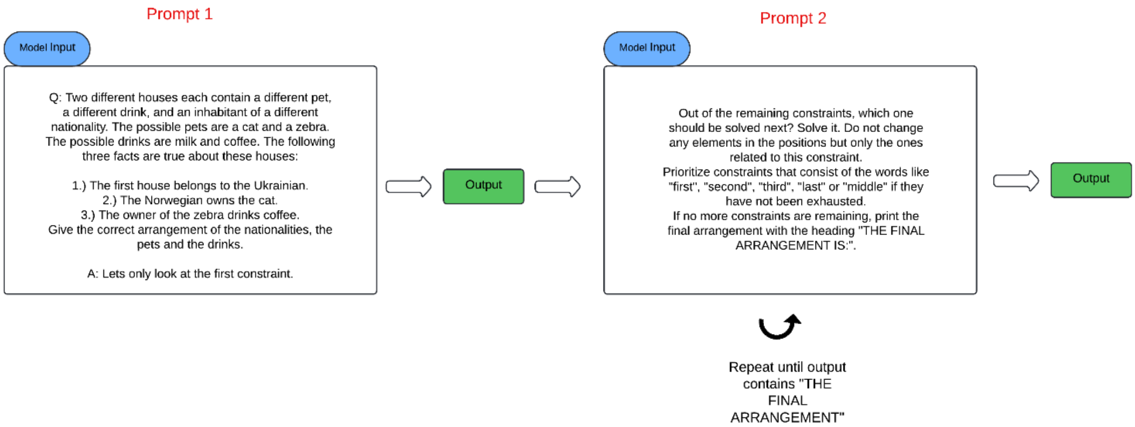

Fig 9. Tree of Thought Prompting with 2 x 3 Puzzle

Fig. 9 shows the process of Tree of Thought. In the first prompt presented to GPT, the text **"Let's only look at the first constraint"** was appended to the prompt, to initialize the process and generate a thought based on the first constraint. Note that this technique requires a direct constraint (one that places an element directly to a position) to be first. For example, in Fig. 9, constraint 1, directly places the Ukrainian in the first house.

Similar to **Yao, S. et al.** [**13**], a thought generator and an evaluator were added to this technique. The second prompt acts as a thought generator. This prompt enables GPT to select a suitable constraint to solve next. The direct constraints often contain words such as "first" and "second" and therefore GPT was instructed to prioritize those constraints first. Finally, to evaluate the end of the process, GPT was instructed to print the arrangement with a specific format.

At each level, a maximum of 3 thoughts were allowed to be generated. At the end of each though, GPT was asked to check the deduced arrangement with the constraints (see system instructions). This acted as a value evaluator of the thoughts. If any constraints were broken in the intermediate steps, another thought at that level was generated. If three thoughts had been generated at one level, a backtrack was performed and more thoughts were generated on the previous level.

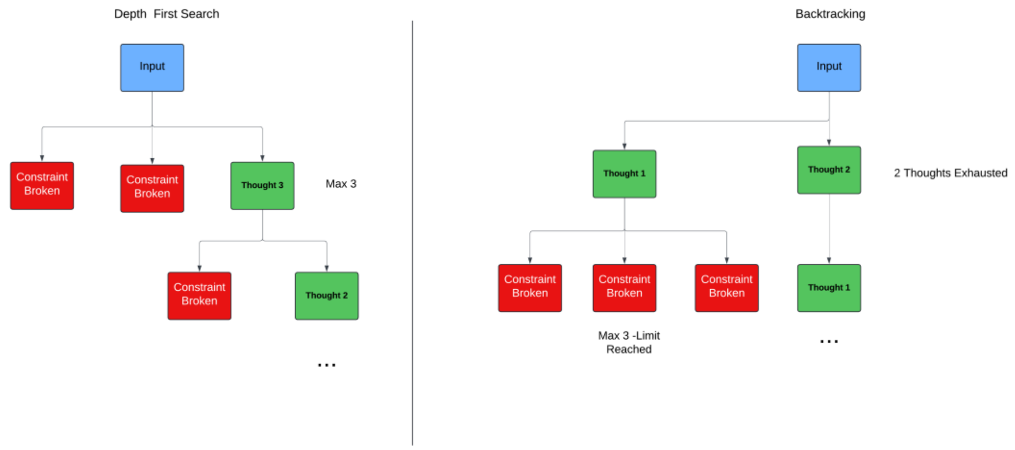

Fig 10. Tree of Thought DFS and Backtracking

The thoughts were generated in a depth-first search manner, hence if the first generated thought did not break any constraint, the thought for the next constraint was generated. This process continued until GPT answered with the final prompt.

In the system window, the following instructions were added:

"You are a helpful assistant. Only solve one constraint at a time. Print the deduced arrangement at the beginning of every answer and then evaluate against every constraint if the newly deduced arrangement breaks any constraints. If it breaks any constraints print a line "Constraints broken", else do nothing. "

This instruction provided a way to know which elements had already been deduced in the arrangement. At the start of every output, GPT printed the arrangement that was already deduced from the solved constraints. Additionally, the constraint check instruction acted as an evaluator to each thought.

This mechanism allowed GPT to solve a constraint and detect if any constraints had been broken. If this was the case either new thoughts were generated if all the thoughts had not been exhausted (max 3) or backtracking was applied to create a new branch.

3.4 Approach 2: NL to Prolog

3.4.1 Zero Shot Chain of Thought (ZS CoT)

The Zero Shot Chain of Thought (ZS CoT) utilizes the Chain of Thought prompting, similar to the NL to NL approach. The final question in each of the puzzles was changed so that the output was a Prolog code. This approach attempted to test if GPT was able to create code from scratch without any additional help.

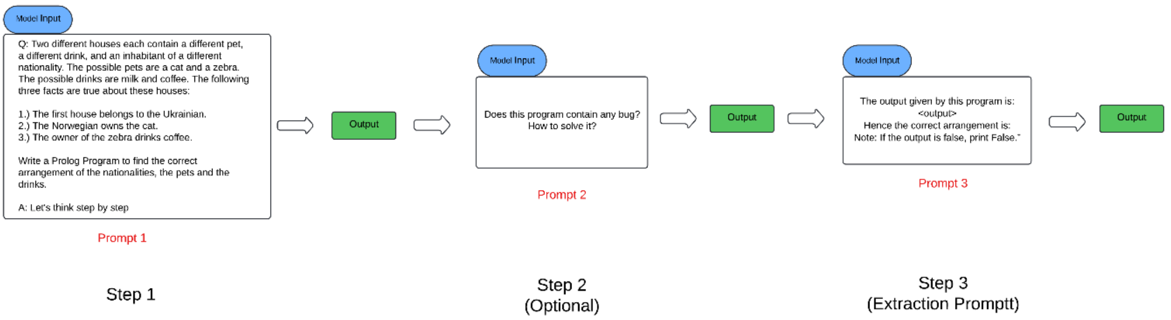

Fig 11. Zero Shot Chain of Thought Prompting with 2 x 3 Puzzle

In the instruction window, GPT was instructed to play the role of a constraint optimization expert.

"Assume you are a constraint optimization expert and you need to model a constraint satisfaction problem in Prolog."

This technique was implemented in two steps:

Step 1: Apply Zero Shot Chain of Thought Prompting

Figure 11 shows the structure of the prompt (Prompt 1) used in this step. The output returned by GPT for this prompt was a Prolog code. Oftentimes the answers needed to be manually created from the outputs because they contained natural language.

Step 2: Solving Bugs

As discussed in the Related Work section, GPT has shown high efficiency in solving bugs in codes. Similar to the approach taken by **Sobania, D. et al**. [**16**], the second prompt aimed to offer GPT a chance to correct any bugs in the code that it produces. Note that this step was optional and only applied if the code in Step 1 did not solve the puzzle. A prompt with the following words "Does this contain any bug? How to solve it?" was used to enable GPT to find and fix bugs in its earlier output.

3.4.2 One Shot Plan and Solve Prompting (OS PS)

Zero Shot Prompting did not allow the user to specify the formatting or the structural formulation of the program. This enabled GPT to use a diverse set of ways to write the code for model optimization which increased the randomness of the output.

In One Shot Plan and Solve (OS PS) prompting, a solved example (as a Plan and Solve prompt) of a puzzle is appended to the prompt. This should decrease the randomness of the programs as well as allow it to learn and structure the output similar to the example.

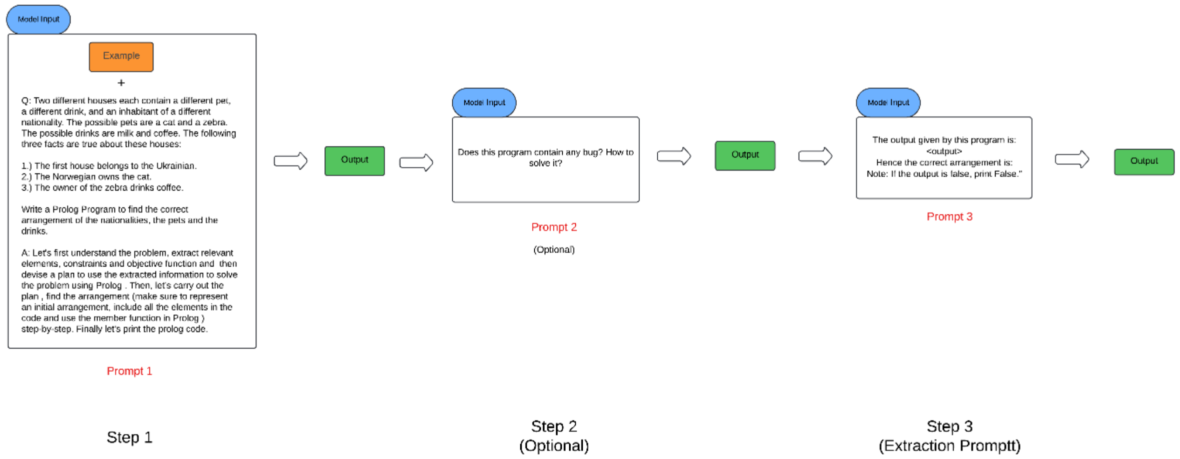

Fig 12. One Shot Plan and Solve Prompting with 2 x 3 Puzzle

Two steps were carried out to obtain the final code:

Step 1: Apply One Shot Plan and Solve Prompting

The 3x2 puzzle was used as an example. This puzzle is not too easy (such that GPT would not have all the information to approach more complex puzzles) and not too complex (such that GPT is provided with more information than it should be).

Similar to **Wang, L. et al.** [**6**], the following text was utilized as a part of the Plan and Solve prompt:

*"Let's first understand the problem, **extract relevant elements, constraints and objective function** and then devise a plan to **use the extracted information to solve the problem using Prolog** . Then, let's carry out the plan **, find the arrangement (make sure to represent an initial arrangement, include all the elements in the code and use the member function in Prolog)** step-by-step. Finally, let's **print the Prolog code**."*

A solution was manually created for the example. A preferred format was used for GPT to imitate.

"Q: There are three people standing in a queue. Each person owns a different pet and is an inhabitant of different nationality. The possible pets are a snail, a jaguar and a zebra. The possible nationalities are Japanese, Spaniard and English. No three people own the

same pets or are an inhabitant of a the same nationality. The following facts are true about this queue:

1. The first person in the queue owns the snail.
2. The Spaniard is in the middle.
3. The English is not the last person in the queue.
4. The last person in the queue does not own the jaguar.
5. The Japanese is immediately behind the jaguar owner.

What is the arrangement of the queue?

A: Let's first understand the problem, extract relevant elements, constraints and objective function and then devise a plan to use the extracted information to solve the problem using Prolog . Then, let’s carry out the plan , find the arrangement (make sure to represent an initial arrangement, include all the elements in the code and use the member function in Prolog) step-by-step. Finally, let's print the Prolog code.

ELEMENTS:

Nationalities:(English, Spaniard, Japanese)
Pets:(snail, jaguar, zebra)

CONSTRAINTS:

a. The first person in the queue owns the snail.
b. The Spaniard is in the middle.
c. The English is not the last person in the queue.
d. The last person in the queue does not own the jaguar.
e. The Japanese is immediately behind the jaguar owner.

OBJECTIVE FUNCTION:

In this problem our objective is not to minimize or maximize any quantity, rather it is to find an arrangement that satisfies all the constraints.

PLAN:

1. We'll use Prolog's "member" predicate to map each person with their nationality and pet.

2. Prolog’s "member" predicate can also be used to structure the constraints of the problem, to fulfills the facts mentioned above.
3. Base case is to declare a rule that represents the queue with three people having different nationalities & different pets.
4. We will represent all the elements using the "member" predicate.

Let's convert this plan to Prolog code.

```prolog
solution(People) :-

% Arrangement
People = [person(1, _, _), person(2, _, _), person(3, _, _)],

% Ensure each property appears exactly once
member(person(1, _, _), People),
member(person(2, _, _), People),
member(person(3, _, _ ), People),
member(person(_ , english, _), People),
member(person(_ , spaniard, _), People),
member(person(_ , japanese, _), People),
member(person(_, _, zebra), People),
member(person(_, _, jaguar), People),
member(person(_, _, snail), People),

% Enforce the constraints
member(person(1, _, snail), People),
member(person(2, spaniard, _), People),
member(person(PositionE, english, _), People), PositionE \= 3,
member(person(PositionJ, _, jaguar), People), PositionJ \= 3,
member(person(PositionJP, japanese, _), People),
PositionJplus1 is PositionJ + 1, PositionJP =:= PositionJplus1.
```

This code models all conditions of the problem.

Please run the Prolog command `?- solution(List).` to solve the problem.”

This format took inspiration from **Tsouros, D. et al.** [**15**] and instructed GPT to extract all the relevant information such as the elements, constraints, and objective as the first step. Then, a plan explained how the puzzle is solved using the 'member' predicate from Prolog. Finally, the code was presented in a preferred format that is easy to understand.

Note that an additional Prolog predicate to define relationships between elements was not used. This was done to keep the example simple and allow GPT to learn quickly. A simpler method was provided by using numbers to define relative positions in the arrangement.

Step 2: Solving Bugs

The second step allowed GPT to correct any bugs in its output**.** In the system instruction window, the following instructions were added:

"Assume you are a constraint optimization expert and you need to model a constraint satisfaction problem in Prolog. If printing the elements, constraints, objective function and plan use the format:

"ELEMENTS:
CONSTRAINTS:
OBJECTIVE FUNCTION:
PLAN:"
Do not use the write function from Prolog when you are coding in Prolog."

The first part of the system instruction is similar to the previous technique. In this prompt, instructions were added for GPT to format the output in a specific way so that it clearly stated its output in the format of the example. GPT was also instructed to not use the write function because it did not work on the system used to verify the code.

3.5 Solution Extraction - Prolog to NL

As a last step in the above two prompting techniques (Step 3), a prompt is used to extract the arrangement given by the Prolog programs in natural language.

For the extraction prompt, the following format was used :

"The output given by this program is:
<output>
Hence the correct arrangement is:
Note: If the output is false, print False."

As a response to this prompt, GPT printed the arrangement given by the Prolog code. Note that SWI-Prolog does not always give a valid arrangement. The response can also be false. For this case, a note was provided to GPT that instructed it to print false in case the output of the program was false.

For example, if the output for the 3x3 puzzle is used in the extraction prompt:

"The output given by this program is:
[h(english,snail,orangeJuice), h(spaniard,jaguar,milk), h(japanese,zebra,coffee)]
Hence the correct arrangement is:
Note: If the output is false, print False."

The response returned by GPT is :

"Based on the output of the program, the correct arrangement of the queue is as follows:
1. First in the queue is the English individual who owns a snail and drinks Orange Juice.
2. In the middle of the queue is the Spaniard who owns a Jaguar and drinks Milk.
3. Lastly, the Japanese individual who owns a Zebra and drinks Coffee.
If the result is False, it indicates that no arrangement of the nationalities, pets, and drinks satisfies all the given constraints.

Note: The 'Maximum Length' parameter was maintained at 256 for Prompt 3. This is because if the length was fixed to a high value like 5000, GPT would not print False and instead print a reason why the solution could be False. Hence to increase discipline, the value was maintained at 256.

4

Evaluation

4.1 Evaluation Method

4.1.1 NL to NL

All the puzzles were evaluated ten times using each technique – Zero Shot, Zero Shot Chain of Thought, and Tree of Thought. The puzzle arrangements in GPT's outputs were evaluated on two main factors:

- **Accuracy (The number of correct answers):** The arrangement was marked as correct if all the elements of the puzzle were present in their correct positions and the explanation for the arrangement was logically correct.
- **The number of tokens used:** The number of words used in the promptings was calculated and an estimate of the number of tokens was calculated. OpenAI describes that ¾ words are equal to 1 token [**37**]. This estimate was used to calculate the tokens in the output.

For Tree of Thought Prompting, additional evaluation was carried based on the average number of backtracks. This would help in evaluating the efficiency of constraint checks as an evaluator.

The average number of backtracks was calculated as:

Backtracks in 10 attempts of a puzzle / 10

4.1.2 NL to Prolog

All the puzzles were evaluated ten times for each technique. The following metrics were calculated:

- **Accuracy (The number of correct answers)**: The output(Prolog code) was marked as correct if it produced the right arrangement without any changes to the Prolog code.

- **The number of correct answers for Prompt 1**: This number was incremented if the first output returned by the AI model contained correct code.
  Note that for easy puzzles such as 2x2 and 2x3, the model often directly made arrangements with the elements already in the correct positions. This was marked as correct because the end solution was correct.

- **The number of correct answers for Prompt 2:** This number was incremented if the second output (returned after Prompt 2 : "Does this program have any bugs? How to solve them?") produced a code that gave the correct arrangement.

- **Classification of code fix requests:** GPT gave different types of responses when it was asked to debug the code. Similar to **Sobania, D. et al.** [**16**], new classes were created that represented the benchmark for the evaluation of the code fix request:

  - **No bug found:** Does not find any bug in the code.
  - **Correct Fix Provided:** Provides a code that gives the correct arrangement.
  - **Tries to Fix something else:** Does not find the bug and tries to solve something else unnecessarily.
  - **Provides a fix but introduces new bug:** Provides a fix for the code but the new code contains another bug.
  - **Alternative implementation:** Does not fix the bug, but gives a second implementation of the code to use instead.

4.2 Results

4.2.1 NL to NL

Table 3 shows the accuracy of GPT for NL to NL approach.

Table 3. Accuracy of GPT (Out of 16 X 10 = 160 attempts)

	Accuracy (Total:160)
ZS	20.6%
ZS CoT	45%
ToT	50%

As we can observe from Table 3, both Zero Shot Chain of Thought and Tree of Thought improved the performance of GPT. Zero Shot Chain of Thought improved the performance by 24.4% whereas Tree of Thought improved it by a staggering 30.4%. Hence prompt engineering has elicited some degree of reasoning in GPT.

One thing to note here is that even though ToT prompting showed a 5% improvement from ZS CoT prompting, this is true only for easy (subjects <=2) & medium-complexity (subjects <=4) puzzles. A full breakdown of how these techniques scaled with different complexities can be seen in Fig. 13. Both ZS CoT and ToT prompting did not return even a single correct arrangement in ten attempts for complexities 4x5, 5x3, 5x4, and 5x5. This might be due to the high number of elements (>=15) that need to be positioned in the arrangement. More elements require a higher number of words and reasoning which increases the chances of logical error and hallucinations.

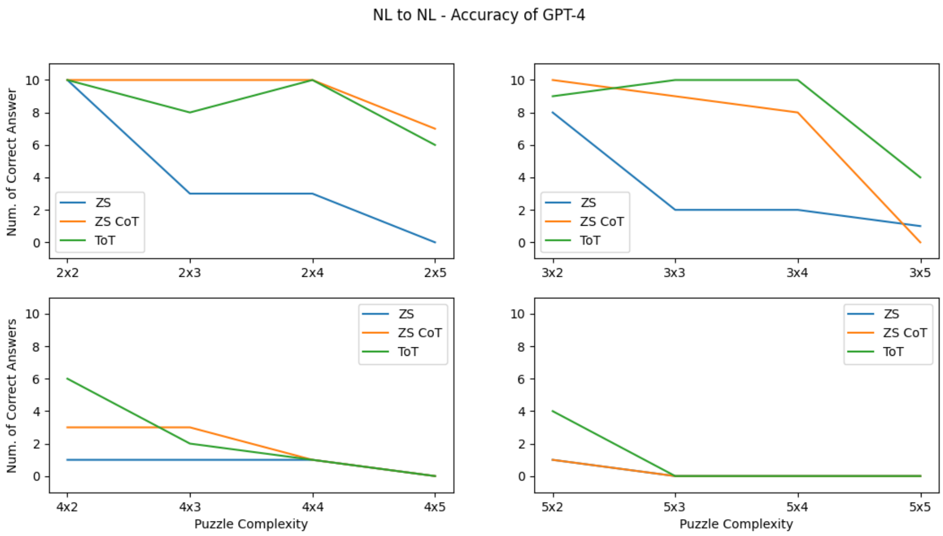

Fig 13 . Accuracy of GPT-4 for NL to NL Approach

Out of all the techniques, ToT prompting performed the best, however the linguistic cost of ToT was higher than other techniques as shown in Table 4. ZS CoT prompting performed slightly poorly but was not as expensive as Tree of Thought, which indicates Chain of Thought is a better option. Below, Table 4 shows the average number of tokens used in the prompt techniques. As we can see, ToT is a very expensive process, mainly because a large number of words are needed to reason about every single constraint.

Table 4. Average Number of Tokens used in NL to NL Prompting Techniques

Subjects	**Categories**			
	2	**3**	**4**	**5**
2	17 (**ZS**) 133(**ZS CoT**) 154(**ToT**)	27 302 382	53 362 587	145 405 761
3	72.1 353 678	80 410 979	778 549 1887	140 684 2564
4	200 558 828	231 567 1694	242 703 2228	298 723 4337
5	117 517 2174	186 674 2843	17 833 5361	117 665 5410

At the time of writing this dissertation, the cost of 1000 output tokens in GPT-4 is $0.06 [**37**]. This indicates that the average cost to carry out a single Tree of Thought prompting with the 5X5 complexity puzzle was $0.32 or $3.2 for the ten attempts. If we observe Fig. 13 and Table 4, we can see that for the 4 x 3 complexity puzzle, ZS CoT prompting gave almost the same accuracy as ToT (3 vs 2), but ToT used as much as 3 times the number of tokes (567 vs 1694) in ZS CoT. For puzzles more complex than this, ToT was only able to display a greater accuracy for 4 x 2 puzzle, which indicates that ToT prompting is not a viable option.

Additionally, Tree of Thought was linguistically expensive due to the backtracking mechanism. Table 5 shows the average number of backtracks performed in ToT.

Table 5. Average Number of Backtracks by GPT in Tree of Thought

Subjects	Characteristics			
	2	**3**	**4**	**5**
2	0(0) **avg(max)**	0(0)	0(0)	0(0)
3	0(0)	0(0)	0(0)	0(**2**)
4	0(0)	0(0)	0(0)	0(**2**)
5	0(**3**)	0(**3**)	0(**2**)	0(**2**)

As we can observe, the average number of backtracks remained at zero for all the puzzles. This, coupled with the accuracy of ToT prompting in Fig. 13 indicates that GPT did not perform well in catching instances of broken constraints. Such an evaluator was untrustworthy, which was one of the main reasons that GPT continued to explore the wrong branches in a tree. In most of the attempts, even if a constraint was broken, GPT hallucinated and printed that all the constraints passed.

One of the common weaknesses of GPT among all the techniques was that it did not consider elements in a position on a case-by-case basis. For example, let us take a look at a scenario in the 4x2 puzzle:

Let us say that GPT deduced an arrangement:

Position 1 : _, snail ,
Position 2 : Spaniard, _
Position 3: _, _
Position 4: _, _

Next it solves the constraint:

"The Japanese is standing behind the Jaguar owner"

GPT deduces this with :

"According to the fourth fact, the person standing immediately in front of the Japanese owns the Jaguar, so the Jaguar owner cannot be in the fourth place because if the Jaguar owner was in the fourth place, the Japanese who stands after the Jaguar owner would have to be in the fifth place which is not possible since there are only four people. Therefore, the fourth person has to be the Japanese."

Here GPT does not consider all the possible positions for the jaguar owner. It assigns the jaguar owner to the fourth position and deems it to be true and continues.

4.2.2 NL to Prolog

Note that the 3x2 puzzle has been left out of the evaluation for this approach as it was used as an example in One Shot Plan and Solve prompting. Hence the results have been evaluated on a total of 15 puzzles.

Table 6 displays the overall accuracy of GPT in generating the correct Prolog program to resolve the puzzle.

Table 6. Accuracy of GPT (Out of 15 X 10 = 150 attempts)

	Accuracy (Total:150)
ZS CoT	23.3%
OS PS	51.3%

As we can see, One Shot Plan and Solve prompting had a 28% higher accuracy than Zero Shot Chain of Thought prompting. This performance can be attributed to the fact that the example provided to GPT helped it structure and create better programs. This indicates that GPT can learn from the provided example and provide better outputs.

Fig. 14 shows the full breakdown of how these two prompting techniques perform with different complexities:

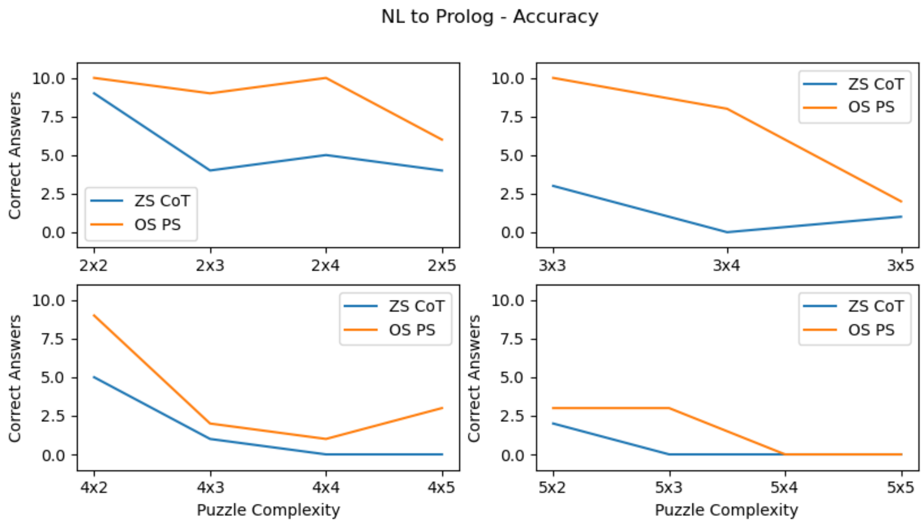

Fig 14 . Accuracy of GPT-4 for NL to Prolog Approach

From Fig. 14 we can observe that OS PS prompting performed better than ZS CoT. Even for complex puzzles like 5x2 and 5x3, GPT was able to write the correct code 3 times with OS PS.

A large performance boost can be seen in the puzzles with 3 subjects where GPT had a high accuracy with the second approach. This shows that training GPT with one example alone can enhance its performance.

Out of all the correct attempts, not all were produced correctly with the first prompt. With the second prompt "Does this code have a bug? How to solve it", GPT corrected its incorrect programs 20 times for each technique. Fig. 15 shows the number of responses GPT got correct in the first attempt (Prompt 1) and the second attempt (Prompt 2).

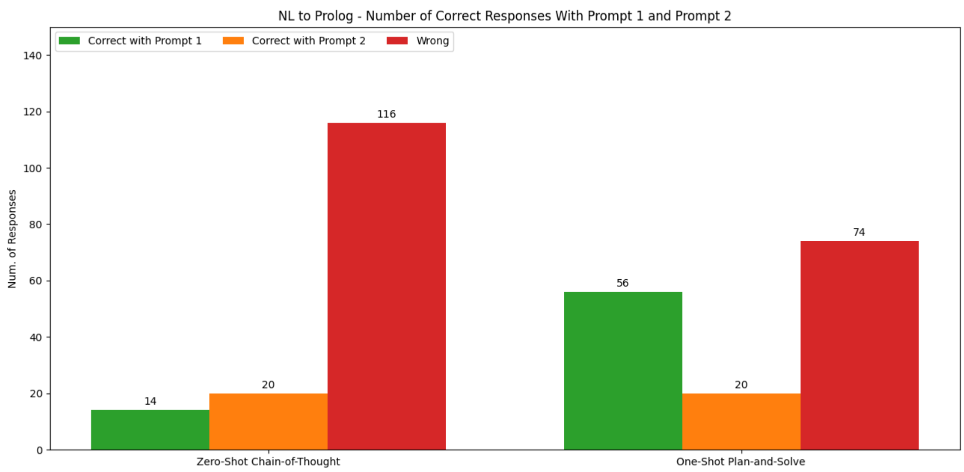

Fig 15. Number of Correct Arrangements With and Without Corrections

As we can see from Fig. 15, GPT was able to find and fix 20 bugs in each prompt technique. However, there was a huge increase (+ 42) in the number of correct arrangements it returned correct in its first attempt in One Shot Plan and Solve prompting.

The incorrect responses returned by GPT were due to various reasons which are classified in the figure below.

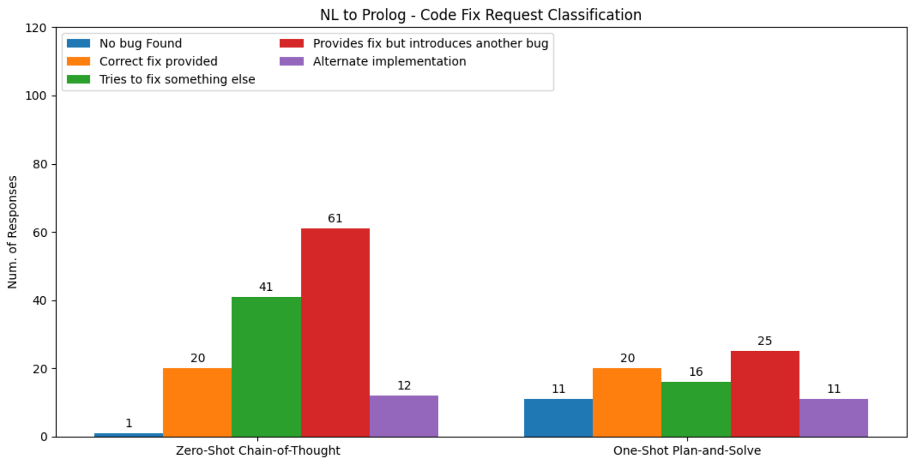

Fig 16 . Code Fix Request Classification

From Fig. 16 we can observe that there is a high number of classifications with "Provides a bug but introduces another bug' and 'Tries to fix something else'. This is particularly high in Zero Shot Chain of Thought where GPT had to come up with a program from scratch. Because there was no fixed format provided, GPT struggled to find bugs and therefore made more mistakes in fixing them (61 vs 25). Whereas in the case of One Shot Plan and Solve, the classification is spread equally amongst all the classes. Note that for OS PS prompting, the number of "No bug Found" classification is higher than ZS CoT prompting (11 vs 1). This was because the example used in OS PS prompting was not scalable. The format of the example listed all the domain constraints before the puzzle constraints. This created an enormous search space which did not bode well with the backtracking mechanism of Prolog.

The scalability of the example provided in the example prompt of One Shot Plan and Solve played a huge factor in GPT solving high-complexity puzzles. There were instances where the code produced was correct, but due to the non-scalability of the solution formed by the format of the example, the solution did not execute in time.

The number of tokens used in these techniques was comparable to the NL to NL approach but not as high as Tree of Thought.

Table 7 shows the average number of tokens used by the two techniques:

Table 7. Average Number of Tokens used in NL to Prolog Prompting Techniques

Subjects	Characteristics			
	2	**3**	**4**	**5**
2	338 (**ZS CoT**) 324 (**OS PS**)	479 322	589 569	605 593
3	N/A	595 467	765 625	915 1212
4	624 595	672 886	800 1127	955 1271
5	740 685	737 855	1541 1142	1205 1217

As we can observe, the cost of both the promptings is similar, however, the tokens used here are significantly less than the ones used in the Tree of Though prompting in NL to NL.

4.3 Comparing NL to NL and NL to Prolog

One Shot Plan and Solve prompting gave the highest accuracy for NL to Prolog approach and Tree of Thought prompting was the best approach for NL to NL. OS PS prompting gave a higher accuracy and used a significantly smaller number of tokens (see Fig. 17).

This is because writing a constraint optimization program does not require abilities like interrelated deductions and backtracking, both of which GPT struggled with. Further, conversing in natural language was financially expensive in techniques like Tree of Thoughts.

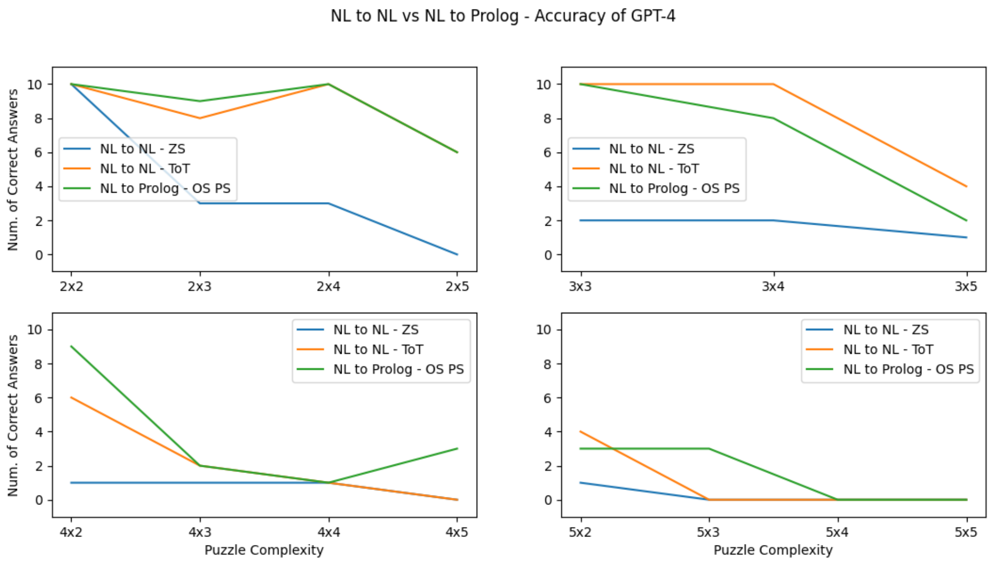

Fig 17. Comparing ToT from NL to NL & OS PS from NL to Prolog Approach

From Fig. 17 we can observe that OS PS prompting in NL to Prolog achieved a higher accuracy in 2, 4, and 5 subject puzzles and comparable accuracy in 3 subject puzzles than NL to NL's ToT approach. More importantly, OS PS prompting enabled GPT to create programs for 4 x 5 and 5X 3 puzzles where all other techniques failed.

Hence NL to Prolog when combined with One Shot Plan and Solve was the best out of all the tested approaches. GPT was able to learn from the provided example and write satisfactory constraint satisfaction programs. Further, this performance was increased using a second prompt that allowed it to find and fix the bugs in the output.

GPT performed well in writing code by learning from an example as well as in finding and fixing bugs. Additionally, with this approach, it was able to solve more complex puzzles such as 4x5 and 5x3.

5

Conclusion

In this dissertation, we investigated the limitations of GPT-4 in solving zebra puzzles and applied two different approaches combined with multiple prompt engineering techniques to enhance its performance.

For the NL to NL approach, GPT showed an accuracy of 45% with ZS CoT prompting and 50% for ToT prompting. This accuracy was higher for puzzles with 2 and 3 subjects. Its reasoning abilities were hindered in more complex puzzles due to hallucinations and illogical deductions. In the NL to Prolog approach, GPT showed an accuracy of 23.3% with ZS CoT prompting and 51.3% for OS PS prompting. With OS PS prompting, it was able to create correct programs for 4x5 and 5x3 puzzles.

Tree of Thought achieved the best accuracy in the NL to NL approach. However, due to the high number of tokens required in the process and the absence of a satisfactory evaluator of thoughts, this technique was not deemed to be the best.

The NL to Prolog approach when combined with One Shot Plan and Solve prompting was the best out of all the tested approaches. GPT was able to learn from the provided example and write satisfactory programs. Further, GPT's performance was enhanced using a second prompt that allowed it to find and fix the bugs in the output.

Further Work

As a future work, more techniques like the Tree of Thought can be explored with the second approach. Another interesting aspect would be to investigate the efficiency of Few Shot prompting with more examples. New tools such as GPT builders that can be fine-tuned and trained for specific purposes may provide even better performance than using prompt engineering alone.

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Appendix

Section 1: Zebra Puzzles

The following section lists the sixteen zebra puzzles used in this dissertation, their solutions and the Prolog program to verify them.

2 X 2 :

Two different houses each contain a different pet. The possible pets are a dog and a cat. The following facts are true about these houses:

1.) One house is blue, and the other is red.

2.) The owner of the red house owns the dog.

Give the correct pairing of the house colors and the pets in those houses.

Solution:

House Color	Blue	Red
Pet	Cat	Dog

Prolog Program:

```
% h(Color,Pet)
solution(Hs) :-

length(Hs, 2),
member(h(red,_), Hs),
member(h(blue,_), Hs),
member(h(_,cat), Hs),

% constraints
member(h(red,dog), Hs). % 1
```

2 X 3 :

Two different houses each contain a different pet, a different drink, and an inhabitant of a different nationality. The possible pets are a cat and a zebra. The possible drinks are milk and coffee. The following three facts are true about these houses:

1.) The first house belongs to the Ukrainian.

2.) The Norwegian owns the cat.

3.) The owner of the zebra drinks coffee.

Give the correct arrangement of the nationalities, the pets and the drinks.

Solution:

	House 1	House 2
Nationality	Ukrainian	Norwegian
Pet	Zebra	Cat
Drink	Coffee	Milk

Prolog Program:

```
% h(Nationality, Pet, Drink)
solution(Hs) :-
length(Hs, 2),

member(h(_,_,milk), Hs),

% constraints
Hs = [h(ukrainian,_,_),_], %1
member(h(norwegian,cat,_), Hs), %2
member(h(_,zebra,coffee), Hs). %3
```

2 X 4 :

Two houses of different colors each contain a different pet, a different drink, and an inhabitant of a different nationality. The possible pets are a cat and a zebra. The possible drinks are milk and coffee. The possible house colors are red and blue. The possible nationalities are Ukrainian and Norwegian. The following four facts are true about these houses:

1.) The first house belongs to the Ukrainian.

2.) The Norwegian owns the cat.

3.) The owner of the zebra drinks coffee.

4.) The owner of the red house drinks milk.

Give the correct arrangement of the nationalities, pets, house colors, and drinks.

Solution:

	House 1	House 2
Nationality	Ukrainian	Norwegian
Pet	Zebra	Cat
Drink	Coffee	Milk
House Color	Blue	Red

Prolog Program:

```
% h(Nationality, Pet, Drink, Color)
solution(Hs) :-
length(Hs, 2),

member(h(_,_,_,blue), Hs),

% constraints
Hs = [h(ukrainian,_,_,_),_], %1
member(h(norwegian,cat,_,_), Hs), %2
member(h(_,zebra,coffee,_), Hs), %3
member(h(_,_,milk,red), Hs). %4
```

2 X 5 :

Two different houses, each with different colors, contain a different pet, a different drink, a different brand of cigarette and an inhabitant of a different nationality. The possible pets are a cat and a zebra. The possible drinks are milk and coffee. The possible house colors are red and blue. The possible brands of cigarettes are Kools and Parliaments. The possible nationalities are Ukrainian and Norwegian. The following five facts are true about these houses:

1.) The first house belongs to the Ukrainian.

2.) The Norwegian owns the cat.

3.) The owner of the zebra drinks coffee.

4.) The owner of the red house drinks milk.

5.) The owner of the blue house smokes Kools.

Give the correct arrangement of the nationalities, pets, house colors, cigarettes and drinks.

Solution:

	House 1	House 2
Nationality	Ukrainian	Norwegian
Pet	Zebra	Cat
Drink	Coffee	Milk
House Color	Blue	Red
Cigarette Brand	Kools	Parliaments

Prolog Program:

```
% h(Nationality, Pet, Drink, Color, Cigarette)
solution(Hs) :-
length(Hs, 2),

member(h(_,_,_,_,parliaments), Hs),

% constraints
Hs = [h(ukrainian,_,_,_,_),_], %1
member(h(norwegian,cat,_,_,_), Hs), %2
member(h(_,zebra,coffee,_,_), Hs), %3
member(h(_,_,milk,red,_), Hs), %4
member(h(_,_,_,blue,kools), Hs). %5
```

3 X 2 :

There are three people standing in a queue. Each person owns a different pet and is an inhabitant of different nationality. The possible pets are a snail, a jaguar and a zebra. The possible nationalities are Japanese, Spaniard and English. No three people own the same pets or are an inhabitant of the same nationality. The following facts are true about this queue:

1. The first person in the queue owns the snail.

2. The Spaniard is in the middle.

3. The English is not the last person in the queue.

4. The last person in the queue does not own the jaguar.

5. The Japanese is immediately behind the jaguar owner.

Give the correct arrangement of the nationalities and their the pets in the queue.

Solution:

	Person 1	Person 2	Person 3
Nationality	English	Spaniard	Japanese
Pet	Snail	Jaguar	Zebra

Prolog Program:

```
% h(Nationality, Pet)
solution(Hs) :-
length(Hs, 3),

member(h(english,_),Hs),
member(h(_,zebra),Hs),

% constraints
Hs = [h(_,snail),_,_], %1
Hs = [_,h(spaniard,_),_],  %2
behind(h(_,jaguar),h(japanese,_),Hs), %5
Hs \= [_,_,h(english,_)],  %3
Hs \= [_,_,h(_,jaguar)]. %4

behind(A, B, Ls) :- append(_, [A,B|_], Ls).
```

3 X 3 :

There are three people standing in a queue. Each person owns a different pet, drinks a different beverage and is an inhabitant of different nationality. The possible pets are a snail, a jaguar and a zebra. The possible beverages are Orange juice, milk and coffee.The possible nationalities are Spaniard, English and Japanese. The following facts are true about this queue:

1. The first person in the queue owns the snail.

2. The Spaniard is standing in the middle

3. The English is not the last person in the queue.

4. The last person in the queue drinks coffee.

5. The Spaniard does not drink orange juice.

6. The last person in the queue does not own the jaguar.

Give the correct arrangement of the nationalities, the pets and the drinks.

Solution:

	Person 1	Person 2	Person 3
Nationality	English	Spaniard	Japanese
Pet	Snail	Jaguar	Zebra
Drink	Orange Juice	Milk	Coffee

Prolog Program:

```
% h(Nationality, Pet, Drink)
solution(Hs) :-
length(Hs, 3),

member(h(english,_,_),Hs),
member(h(japanese,_,_),Hs),
member(h(_,_,orangeJuice),Hs),
member(h(_,_,milk),Hs),
member(h(_,zebra,_),Hs),
member(h(_,jaguar,_),Hs),

% constraints
Hs = [h(_,snail,_),_,_], %1
```

```
Hs = [_,h(spaniard,_,_),_], %2
Hs = [_,_,h(_,_,coffee)], %4
Hs \= [_,_,h(english,_,_)], %3
\+ member(h(spaniard,_,orangeJuice),Hs),%5
Hs \= [_,_,h(_,jaguar,_)]. %6

behind(A, B, Ls) :- append(_, [A,B|_], Ls).
```

3 X 4 :

There are three people standing in a queue. Each person owns a different pet, drinks a different beverage, lives in a different colored house and is an inhabitant of different nationality. The possible pets are a snail, a jaguar and a zebra. The possible nationalities are Japanese, Spaniard and English. The possible beverages are Orange juice, milk and coffee. The possible house colors are red, green and ivory. No two people own the same pet, drink the same beverage, live in the same house or are an inhabitant of a the same nationality. The following facts are true about the queue:

1. The first person in the queue owns the snail.

2. The Spaniard is standing in the middle.

3. The English is not the last person in the queue.

4. The last person in the queue drinks coffee.

5. The Spaniard does not drink orange juice.

6. The orange juice drinker lives in the red house.

7. The person who lives in the ivory house is standing immediately in-front of the person who lives in the green house.

8. The last person in the queue does not own the jaguar.

Give the correct arrangement of the nationalities, pets, house colors, and drinks.

Solution:

	Person 1	Person 2	Person 3
Nationality	English	Spaniard	Japanese
Pet	Snail	Jaguar	Zebra
Drink	Orange Juice	Milk	Coffee
House Color	Red	Ivory	Green

Prolog Program:

```
% h(Nationality, Pet, Drink,Color)
solution(Hs) :-
length(Hs, 3),

member(h(english,_,_,_),Hs),
member(h(japanese,_,_,_),Hs),
member(h(_,_,milk,_),Hs),
member(h(_,zebra,_,_),Hs),
member(h(_,jaguar,_,_),Hs),

% constraints
Hs = [h(_,snail,_,_),_,_], %1
Hs = [_,h(spaniard,_,_,_),_], %2
Hs = [_,_,h(_,_,coffee,_)], %4
member(h(_,_,orangeJuice,red),Hs),%6
behind(h(_,_,_,ivory), h(_,_,_,green),Hs), %7
Hs \= [_,_,h(english,_,_,_)], %3
\+ member(h(spaniard,_,orangeJuice,_),Hs),        %5
Hs \= [_,_,h(_,jaguar,_,_)]. %8

behind(A, B, Ls) :- append(_, [A,B|_], Ls).
```

3 X 5 :

There are three people standing in a queue. Each person owns a different pet, drinks a different beverage, smokes a different brand of cigarette, lives in a different colored house and is an inhabitant of different nationality. The possible pets are a snail, a jaguar and a zebra. The possible beverages are Orange juice, milk and coffee. The possible house colors are red, ivory and green. The possible cigarette brands are Lucky Strike, Parliament and Old Gold. The possible nationalities are Spaniard, English and Japanese. The following facts are true about this queue:

1. The first person in the queue owns the snail.

2. The Spaniard is standing in the middle.

3. The English is not the last person in the queue.

4. The last person in the queue drinks coffee.

5. The Spaniard does not drink orange juice.

6. The orange juice drinker lives in the red house.

7. The person who lives in the ivory house is standing immediately in-front of the person who lives in the green house.

8. The person immediately behind the milk drinker smokes old gold.

9. The snail owner does not smoke Parliaments.

10. The last person in the queue does not own the jaguar.

What is a possible arrangement of the queue that follows all the constraints?

Solution:

	Person 1	Person 2	Person 3
Nationality	English	Spaniard	Japanese
Pet	Snail	Jaguar	Zebra
Drink	Orange Juice	Milk	Coffee
House Color	Red	Ivory	Green
Cigarette Brand	Lucky Strike	Parliaments	Old Gold

Prolog Program:

```
% h(Nationality, Pet, Drink,Color,Cigarette)
solution(Hs) :-
length(Hs, 3),

member(h(english,_,_,_,_),Hs),
member(h(japanese,_,_,_,_),Hs),
member(h(_,zebra,_,_,_),Hs),
member(h(_,jaguar,_,_,_),Hs),
member(h(_,_,_,_,luckyStrike),Hs),
member(h(_,_,_,_,parliaments),Hs),

% constraints
Hs = [h(_,snail,_,_,_),_,_], %1
Hs = [_,h(spaniard,_,_,_,_),_], %2
Hs = [_,_,h(_,_,coffee,_,_)], %4
member(h(_,_,orangeJuice,red,_),Hs),%6
behind(h(_,_,_,ivory,_), h(_,_,_,green,_),Hs), %7
```

```
behind(h(_,_,milk,_,_),h(_,_,_,_,oldGold),Hs), %8
\+ member(h(_,snail,_,_,parliaments),Hs),          %9
Hs \= [_,_,h(english,_,_,_,_)], %3
\+ member(h(spaniard,_,orangeJuice,_,_),Hs),     %5
Hs \= [_,_,h(_,jaguar,_,_,_)]. %10

behind(A, B, Ls) :- append(_, [A,B|_], Ls).
```

4 X 2 :

There are four people standing in a queue. Each person owns a different pet and is an inhabitant of different nationality. The possible pets are a snail, a jaguar, a parrot and a zebra. The possible nationalities are Spaniard, Indian, English and Japanese. The following facts are true about this queue:

1. The first person in the queue owns the snail.

2. The snail owner is standing immediately in-front of the Spaniard.

3. The Indian owns the parrot.

4. The person standing immediately in-front of the Japanese owns the Jaguar.

5. The Japanese is not at the end.

6. The Japanese does not own the snail.

Give the correct arrangement of the nationalities and their the pets in the queue.

Solution:

	Person 1	Person 2	Person 3	Person 4
Nationality	English	Spaniard	Japanese	Indian
Pet	Snail	Jaguar	Zebra	Parrot

Prolog Program:

```
% h(Nationality, Pet)
solution(Hs) :-
length(Hs, 4),

member(h(english,_), Hs),
member(h(japanese,_), Hs),
member(h(_,zebra), Hs),
```

```
Hs = [h(_,snail),_,_,_], %1
behind(h(_,snail),h(spaniard,_), Hs), %2
member(h(indian,parrot), Hs), %3
behind(h(_,jaguar),h(japanese,_), Hs), %4
Hs \= [_,_,_,h(japanese,_)], %5
\+ member(h(japanese,snail), Hs). %6

behind(A, B, Ls) :- append(_, [A,B|_], Ls).
```

4 X 3 :

There are four people standing in a queue. Each person owns a different pet, drinks a different beverage and is an inhabitant of different nationality. The possible pets are a snail, a jaguar, a parrot, and a zebra. The possible beverages are orange juice, milk, bubble tea and coffee. The possible nationalities are Spaniard, Indian, English and Japanese. The following facts are true about this queue:

1. The first person in the queue owns the snail.

2. The snail owner is standing immediately in-front of the Spaniard.

3. The Indian owns the parrot.

4. The person behind the snail owner drinks milk.

5. The last person in the queue drinks bubble tea.

6. The orange juice drinker is standing immediately in-front of the milk drinker.

7. The person standing immediately in-front of the Japanese owns the jaguar.

8. The Japanese is not at the end.

9. The Japanese does not own the snail.

Give the correct arrangement of the nationalities, the pets and the drinks.

Solution:

	Person 1	Person 2	Person 3	Person 4
Nationality	English	Spaniard	Japanese	Indian
Pet	Snail	Jaguar	Zebra	Parrot
Drink	Orange Juice	Milk	Coffee	Bubble tea

Prolog Program:

```
% h(Nationality, Pet, Drink)
solution(Hs) :-
length(Hs, 4),

member(h(english,_,_), Hs),
member(h(japanese,_,_), Hs),
member(h(_,zebra,_), Hs),
member(h(_,_,coffee), Hs),

Hs = [h(_,snail,_),_,_,_], %1
behind(h(_,snail,_),h(spaniard,_,_), Hs), %2
member(h(indian,parrot,_), Hs), %3
behind(h(_,snail,_),h(_,_,milk), Hs),%4
Hs = [_,_,_,h(_,_,bubbleTea)],%5
behind(h(_,_,orangeJuice),h(_,_,milk), Hs),%6
behind(h(_,jaguar,_),h(japanese,_,_), Hs), %7
Hs \= [_,_,_,h(japanese,_,_)], %8
\+ member(h(japanese,snail,_), Hs). %9

behind(A, B, Ls) :- append(_, [A,B|_], Ls).
```

4 X 4 :

There are four people standing in a queue. Each person owns a different pet, drinks a different beverage, lives in a different house and is an inhabitant of different nationality. The possible pets are a snail, a jaguar, a parrot, and a zebra. The possible beverages are Orange juice, milk, bubble tea and coffee. The possible house colors are red, ivory, blue and green. The possible nationalities are Spaniard, Indian, English and Japanese. The following facts are true about this queue:

1. The first person in the queue owns the snail.

2. The snail owner is immediately in-front of the Spaniard.

3. The Indian owns the parrot.

4. The person standing immediately behind the snail owner drinks milk.

5. The last person in the queue drinks bubble tea.

6. The orange juice drinker is standing immediately in-front of the milk drinker.

7. The third person in the queue lives in the green house.

8. The milk drinker is standing immediately behind the owner of the red house.

9. The person standing immediately in-front of the Japanese owns the jaguar .

10. The Japanese is not at the end.

11. The owner of the parrot does not live in the ivory house.

12. The Japanese does not own the snail.

Give the correct arrangement of the nationalities, pets, house colors, and drinks.

Solution:

	Person 1	Person 2	Person 3	Person 4
Nationality	English	Spaniard	Japanese	Indian
Pet	Snail	Jaguar	Zebra	Parrot
Drink	Orange Juice	Milk	Coffee	Bubble tea
House Color	Red	Ivory	Green	Blue

Prolog Program:

```
% h(Nationality, Pet, Drink)
solution(Hs) :-
length(Hs, 4),

member(h(english,_,_,_), Hs),
member(h(japanese,_,_,_), Hs),
member(h(_,zebra,_,_), Hs),
member(h(_,_,coffee,_), Hs),
member(h(_,_,_,blue), Hs),
member(h(_,_,_,ivory), Hs),

Hs = [h(_,snail,_,_),_,_,_], % 1
behind(h(_,snail,_,_),h(spaniard,_,_,_), Hs), %2
member(h(indian,parrot,_,_), Hs), %3
behind(h(_,snail,_,_),h(_,_,milk,_), Hs),%4
Hs = [_,_,_,h(_,_,bubbleTea,_)],%5
behind(h(_,_,orangeJuice,_),h(_,_,milk,_), Hs),%6
Hs = [_,_,h(_,_,_,green),_], %7
behind(h(_,_,_,red),h(_,_,milk,_), Hs), %8
behind(h(_,jaguar,_,_),h(japanese,_,_,_), Hs), %9
```

```
Hs \= [_,_,_,h(japanese,_,_,_)], %10
\+ member(h(_,parrot,_,ivory), Hs),%11
\+ member(h(japanese,snail,_,_), Hs). %12

behind(A, B, Ls) :- append(_, [A,B|_], Ls).
```

4 X 5:

There are four people standing in a queue. Each person owns a different pet, drinks a different beverage, smokes a different brand of cigarette, lives in a different colored house and is an inhabitant of a different nationality. The possible pets are a snail, a jaguar, a parrot and a zebra. The possible beverages are orange juice, milk, bubble tea and coffee. The possible house colors are red, ivory, blue and green. The possible cigarette brands are Lucky Strike, Chesterfield, Parliament and Old Gold. The possible nationalities are Spaniard, Indian, English and Japanese. The following facts are true about this queue:

1. The first person in the queue owns the snail.

2. The snail owner is standing immediately in-front of the Spaniard.

3. The Indian owns the parrot.

4. The person standing behind the snail owner drinks milk.

5. The last person in the queue drinks bubble tea.

6. The orange juice drinker is standing immediately in-front of the milk drinker.

7. The third person in the queue lives in the green house.

8. The owner of the parrot does not live in the ivory house.

9. The milk drinker is standing immediately behind the owner of the red house.

10. The person behind the owner of the red house smokes Chesterfield.

11. The bubble tea drinker smokes Parliaments.

12 The English does not smoke old Gold.

13. The person standing immediately in-front of the Japanese owns the Jaguar.

14. The Japanese is not at the end.

15. The Japanese does not own the snail.

What is a possible arrangement of the queue that follows all the constraints?

Solution:

	Person 1	Person 2	Person 3	Person 4
Nationality	English	Spaniard	Japanese	Indian
Pet	Snail	Jaguar	Zebra	Parrot
Drink	Orange Juice	Milk	Coffee	Bubble tea
House Color	Red	Ivory	Green	Blue
Cigarette Brand	Lucky Strike	Chesterfield	Old Gold	Parliaments

Prolog Program:

```
solution(Hs) :-
length(Hs, 4),

member(h(english,_,_,_,_), Hs),
member(h(japanese,_,_,_,_), Hs),
member(h(_,zebra,_,_,_), Hs),
member(h(_,_,coffee,_,_), Hs),
member(h(_,_,_,blue,_), Hs),
member(h(_,_,_,ivory,_), Hs),
member(h(_,_,_,_,oldGold), Hs),
member(h(_,_,_,_,luckyStrike), Hs),

Hs = [h(_,snail,_,_,_),_,_,_], % 1
behind(h(_,snail,_,_,_),h(spaniard,_,_,_,_), Hs), %2
member(h(indian,parrot,_,_,_), Hs), %3
behind(h(_,snail,_,_,_),h(_,_,milk,_,_), Hs),%4
Hs = [_,_,_,h(_,_,bubbleTea,_,_)],%5
behind(h(_,_,orangeJuice,_,_),h(_,_,milk,_,_), Hs),%6
Hs = [_,_,h(_,_,_,green,_),_], %7
behind(h(_,_,_,red,_),h(_,_,milk,_,_), Hs), %9
behind(h(_,_,_,red,_),h(_,_,_,_,chesterfield), Hs), %10
member(h(_,_,bubbleTea,_,parliament), Hs), %11
behind(h(_,jaguar,_,_,_),h(japanese,_,_,_,_), Hs), %13
Hs \= [_,_,_,h(japanese,_,_,_,_)], %14
\+ member(h(english,_,_,_,oldGold), Hs),%12
\+ member(h(_,parrot,_,ivory,_), Hs),%8
\+ member(h(japanese,snail,_,_,_), Hs). %15

behind(A, B, Ls) :- append(_, [A,B|_], Ls).
```

5 X 2 :

There are five people standing in a queue. Each person owns a different pet and is an inhabitant of different nationality. The possible pets are a snail, a jaguar, a parrot, a cat and a zebra. The possible nationalities are Spaniard, Indian, English, Irish and Japanese. The following facts are true about this queue:

1. The first person in the queue owns the snail.

2. The snail owner is standing immediately in-front of the Spaniard.

3. The Indian owns the parrot.

4. The person directly in front of the Japanese owns the jaguar.

5. The Irish is the last person in the queue.

6. The Japanese does not own the snail.

7. The Japanese is not at the end.

8. The Japanese does not own the cat.

Give the correct arrangement of the nationalities and their the pets in the queue.

Solution:

	Person 1	Person 2	Person 3	Person 4	Person 5
Nationality	English	Spaniard	Japanese	Indian	Irish
Pet	Snail	Jaguar	Zebra	Parrot	Cat

Prolog Program:

```
solution(Hs) :-
length(Hs, 5),

member(h(english,_), Hs),
member(h(japanese,_), Hs),
member(h(_,zebra), Hs),
member(h(_,cat), Hs),

Hs = [h(_,snail),_,_,_,_], %1
behind(h(_,snail),h(spaniard,_), Hs),%2
```

```
member(h(indian,parrot), Hs), %3
behind(h(_,jaguar),h(japanese,_), Hs), %4
Hs = [_,_,_,_,h(irish,_)], %5
\+ member(h(japanese,cat), Hs), %8
Hs \= [_,_,_,_,h(japanese,_)], %7
\+ member(h(japanese,snail), Hs). %6

behind(A, B, Ls) :- append(_, [A,B|_], Ls).
```

5 X 3 :

There are five people standing in a queue. Each person owns a different pet, drinks a different beverage and is an inhabitant of different nationality. The possible pets are a snail, a jaguar, a cat, a parrot, and a zebra. The possible beverages are Orange juice, milk, bubble tea, lemonade and coffee. The possible nationalities are Spaniard, Indian, English, Irish and Japanese. The following facts are true about this queue:

1. The first person in the queue owns the snail.

2. The snail owner is standing immediately in-front of the Spaniard.

3. The Indian owns the parrot.

4. The person standing immediately in-front of the Japanese owns the jaguar.

5. The Irish is the last person in the queue.

6.The Jaguar owner drinks milk.

7. The lemonade drinker is behind the Indian.

8. The person standing immediately in-front of the parrot owner drinks coffee.

9. The Japanese does not own the snail.

10. The Japanese does not own the cat.

11. The English does not drink bubble tea.

Give the correct arrangement of the nationalities, the pets and the drinks.

Solution:

	Person 1	Person 2	Person 3	Person 4	Person 5
Nationality	English	Spaniard	Japanese	Indian	Irish
Pet	Snail	Jaguar	Zebra	Parrot	Cat
Drink	Orange Juice	Milk	Coffee	Bubble tea	Lemonade

Prolog Program:

```
solution(Hs) :-
length(Hs, 5),

member(h(english,_,_), Hs),
member(h(japanese,_,_), Hs),
member(h(_,zebra,_), Hs),
member(h(_,cat,_), Hs),
member(h(_,_,bubbletea), Hs),
member(h(_,_,orangeJuice), Hs),

Hs = [h(_,snail,_),_,_,_,_], %1
behind(h(_,snail,_),h(spaniard,_,_), Hs), %2
member(h(indian,parrot,_), Hs), %3
behind(h(_,jaguar,_),h(japanese,_,_), Hs), %4
Hs = [_,_,_,_,h(irish,_,_)], %5
member(h(_,jaguar,milk), Hs), %6
behind(h(indian,_,_),h(_,_,lemonade), Hs), %7
behind(h(_,_,coffee),h(_,parrot,_), Hs), %8
\+ member(h(japanese,cat,_), Hs), %10
\+ member(h(japanese,snail,_), Hs), %9
\+ member(h(english,_,bubbletea), Hs). %11

behind(A, B, Ls) :- append(_, [A,B|_], Ls).
```

5 X 4 :

There are five people standing in a queue. Each person owns a different pet, drinks a different beverage, lives in a different colored house and is an inhabitant of different nationality. The possible pets are a snail, a jaguar, a cat, a parrot, and a zebra. The possible beverages are orange juice, milk, bubble tea, lemonade and coffee. The possible nationalities are Spaniard, Indian, English, Irish and Japanese. The possible house colors are red, blue, green, ivory and yellow. The following facts are true about this queue:

1. The first person in the queue owns the snail.

2. The snail owner is standing immediately in-front of the Spaniard.

3. The Indian owns the parrot.

4. The person standing immediately in-front of the Japanese owns the jaguar.

5. The Irish is the last person in the queue.

6. The Jaguar owner drinks milk.

7. The lemonade drinker is standing immediately behind the Indian.

8. The coffee drinker lives in the green house.

9. The blue house owner is standing immediately in-front of the yellow house owner.

10. The person standing immediately behind the snail owner lives in the ivory house.

11. The person standing immediately in-front of the parrot owner drinks coffee.

12. The Japanese does not own the snail.

13. The Japanese does not own the cat.

14. The English does not drink bubble tea.

Give the correct arrangement of the nationalities, pets, house colors, and drinks.

Solution:

	Person 1	Person 2	Person 3	Person 4	Person 5
Nationality	English	Spaniard	Japanese	Indian	Irish
Pet	Snail	Jaguar	Zebra	Parrot	Cat
Drink	Orange Juice	Milk	Coffee	Bubble tea	Lemonade
House Color	Red	Ivory	Green	Blue	Yellow

Prolog Program:

```
solution(Hs) :-
length(Hs, 5),

member(h(english,_,_,_), Hs),
member(h(japanese,_,_,_), Hs),
```

```
member(h(_,zebra,_,_), Hs),
member(h(_,_,_,red), Hs),
member(h(_,cat,_,_), Hs),
member(h(_,_,bubbletea,_), Hs),
member(h(_,_,orangeJuice,_), Hs),

Hs = [h(_,snail,_,_),_,_,_,_], %1
behind(h(_,snail,_,_),h(spaniard,_,_,_), Hs), %2
member(h(indian,parrot,_,_), Hs), %3
behind(h(_,jaguar,_,_),h(japanese,_,_,_), Hs), %4
Hs = [_,_,_,_,h(irish,_,_,_)], %5
member(h(_,jaguar,milk,_), Hs), %6
behind(h(indian,_,_,_),h(_,_,lemonade,_), Hs), %7
member(h(_,_,coffee,green), Hs), %8
behind(h(_,_,_,blue),h(_,_,_,yellow), Hs), %9
behind(h(_,snail,_,_),h(_,_,_,ivory), Hs), %10
behind(h(_,_,coffee,_),h(_,parrot,_,_), Hs), %11
\+ member(h(japanese,cat,_,_), Hs), %13
\+ member(h(japanese,snail,_,_), Hs), %12
\+ member(h(english,_,bubbletea,_), Hs). %14

behind(A, B, Ls) :- append(_, [A,B|_], Ls).
```

5 X 5 :

There are five people standing in a queue. Each person owns a different pet, drinks a different beverage, smokes a different brand of cigarette, lives in a different colored house and is an inhabitant of a different nationality. The possible pets are a snail, a jaguar, a parrot, a cat and a zebra. The possible beverages are orange juice, milk, bubble tea, lemonade and coffee. The possible house colors are red, ivory, blue, yellow and green. The possible cigarette brands are Lucky Strike, Chesterfield, Parliament, Kools and Old Gold. The possible nationalities are Spaniard, Irish, Indian, English and Japanese. The following facts are true about this queue:

1. The English is the first person in the queue.

2. The Indian owns the parrot.

3. The lemonade drinker lives in the yellow house.

4. The Spaniard drinks milk.

5. The yellow house owner is immediately behind of the owner of the blue house.

6. The Old Gold smoker owns the Zebra.

7. The Lucky Strike smoker is the owner of the red house.

8. The person in the middle drinks coffee.

9. The Japanese owns the green house.

10. The man who smokes Chesterfields is standing immediately behind the man with the snail.

11. The Lucky Strike smoker is standing immediately in-front of the jaguar owner.

12. The Parliaments smoker drinks bubble-tea.

13. The Irish smokes Kools.

14.The English is standing immediately in-front of the owner of the ivory house.

What is a possible arrangement of the queue that follows all the constraints?

Solution:

	Person 1	Person 2	Person 3	Person 4	Person 5
Nationality	English	Spaniard	Japanese	Indian	Irish
Pet	Snail	Jaguar	Zebra	Parrot	Cat
Drink	Orange Juice	Milk	Coffee	Bubble tea	Lemonade
House Color	Red	Ivory	Green	Blue	Yellow
Cigarette Brand	Lucky Strike	Chesterfield	Old Gold	Parliaments	Kools

Prolog Program:

```
solution(Hs) :-
length(Hs, 5),

member(h(_,_,orangeJuice,_,_), Hs),
member(h(_,cat,_,_,_), Hs),

Hs = [h(english,_,_,_,_),_,_,_,_], %1
member(h(indian,parrot,_,_,_), Hs), %2
member(h(_,_,lemonade,yellow,_), Hs), %3
member(h(spaniard,_,milk,_,_), Hs), %4
behind(h(_,_,_,blue,_),h(_,_,_,yellow,_), Hs), %5
member(h(_,zebra,_,_,oldGold), Hs), %6
```

```
member(h(_,_,_,red,luckyStrike), Hs), %7
Hs = [_,_,h(_,_,coffee,_,_),_,_], %8
member(h(japanese,_,_,green,_), Hs), %9
behind(h(_,snail,_,_,_),h(_,_,_,_,chesterfields), Hs), %10
behind(h(_,_,_,_,luckyStrike),h(_,jaguar,_,_,_), Hs), %11
member(h(_,_,bubbleTea,_,parliaments), Hs), %12
member(h(irish,_,_,_,kools), Hs), %13
behind(h(english,_,_,_,_),h(_,_,_,ivory,_), Hs).

behind(A, B, Ls) :- append(_, [A,B|_], Ls).
```

Section 2: Prompt Engineering Formats

The sections below describes the format of all the prompts engineering techniques used in this dissertation. To make the format easier to read, the puzzles have been represented by {puzzle}. A link to the conversation that demonstrate these techniques in OpenAI Playground environment has also been provided.

Note: The playground examples will open with default parameters. Please change the model parameters to below:

Model : GPT – 4 (ChatGPT Plus Subscription needed)
Temperature: 1
Maximum Length: 5000 or 256 (as specified in implementation)

1. NL to NL

1.1 Zero-Shot

User Prompt

Q: {puzzle}

A:

System Instructions:

You are a helpful assistant.

OpenAI Playground Example:

https://platform.openai.com/playground/p/wYOnYrwXV2FwtCz7bIduZXfZ?model=gpt-4&mode=chat

1.2 Zero-Shot Chain-of-thought

User Prompt

Q: {puzzle}

A: Let's think step by step

System Instructions:

You are a helpful assistant.

OpenAI Playground Example:

https://platform.openai.com/playground/p/g2HxFpqsaPGSGoojIrkvdvGW?model=gpt-4&mode=chat

1.3 Tree of Thought

User Prompt (Prompt 1)

Q: {puzzle: 3 x2 }

A: Let's only look at the first constraint

Prompt 2 :

Out of the remaining constraints, which one should be solved next? Solve it. Do not change any elements in the positions but only the ones related to this constraint. Prioritize constraints that consist of the words like "first", "second", "third", "last" or "middle" if they have not been exhausted. If no more constraints are remaining, print the final arrangement with the heading "THE FINAL ARRANGEMENT IS:".

System Instructions :

You are a helpful assistant. Only solve one constraint at a time. Print the deduced arrangement at the beginning of every answer and then evaluate against every constraint if the newly deduced arrangement breaks any constraints. If it breaks any constraints print a line "Constraints broken", else do nothing.

OpenAI Playground Example:

https://platform.openai.com/playground/p/1AFjvUustb0SwmZ0krjmWpKp?model=gpt-4&mode=chat

2. NL to Prolog

Note: The final question in the puzzles in this approach were modified to obtain a Prolog program instead of the correct arrangement. For example, for the 5x5 puzzle the question "What is a possible arrangement of the queue that follows all the constraints?" was changed to "Write a Prolog program to find the correct arrangement of the queue that follows all the constraints.".

2.1 Zero-Shot Chain-of-thought

User Prompt (Prompt 1)

Q: {puzzle}

A: Let's think step by step

Prompt 2

Does this program have a bug? How to fix it?

Prompt 3 (Extraction Prompt)

The output given by this program is:
<output>
Hence the correct arrangement is:
Note: If the output is false, print False.

System Instructions:

Assume you are a constraint optimization expert and you need to model a constraint satisfaction problem in Prolog.

OpenAI Playground Example:

https://platform.openai.com/playground/p/LwwkRkt8ASV4rtaKqjBPmxHs?model=gpt-4&mode=chat

One-Shot Plan and Solve

Prompt 1

Q:{Puzzle: 3x2}

A: Let's first understand the problem, extract relevant elements, constraints and objective function and then devise a plan to use the extracted information to solve the problem using Prolog . Then, let’s carry out the plan , find the arrangement (make sure to represent an initial arrangement, include all the elements in the code and use the member function in Prolog) step-by-step. Finally let's print the Prolog code.

ELEMENTS:

Nationalities:(English, Spaniard, Japanese)
Pets:(snail, jaguar, zebra)

CONSTRAINTS:

a. The first person in the queue owns the snail.
b. The Spaniard is in the middle.
c. The English is not the last person in the queue.
d. The last person in the queue does not own the jaguar.
e. The Japanese is immediately behind the jaguar owner.

OBJECTIVE FUNCTION:

In this problem our objective is not to minimize or maximize any quantity, rather it is to find an arrangement that satisfies all the constraints.

PLAN:

1. We'll use Prolog's "member" predicate to map each person with their nationality and pet.
2. Prolog’s "member" predicate can also be used to structure the constraints of the problem, to fulfills the facts mentioned above.

3. Base case is to declare a rule that represents the queue with three people having different nationalities & different pets.
4. We will represent all the elements using the "member" predicate.

Let's convert this plan to Prolog code.

```prolog
solution(People) :-

% Arrangement
People = [person(1, _, _), person(2, _, _), person(3, _, _)],

% Ensure each property appears exactly once
member(person(1, _, _), People),
member(person(2, _, _), People),
member(person(3, _, _ ), People),
member(person(_ , english, _), People),
member(person(_ , spaniard, _), People),
member(person(_ , japanese, _), People),
member(person(_, _, zebra), People),
member(person(_, _, jaguar), People),
member(person(_, _, snail), People),

% Enforce the constraints
member(person(1, _, snail), People),
member(person(2, spaniard, _), People),
member(person(PositionE, english, _), People), PositionE \= 3,
member(person(PositionJ, _, jaguar), People), PositionJ \= 3,
member(person(PositionJP, japanese, _), People),
PositionJplus1 is PositionJ + 1, PositionJP =:= PositionJplus1.
```

This code models all conditions of the problem. Please run the Prolog command `?-solution(List).` to solve the problem."

Q: {puzzle}

A: Let's first understand the problem, extract relevant elements, constraints and objective function and then devise a plan to use the extracted information to solve the problem using Prolog . Then, let’s carry out the plan , find the arrangement (make sure to represent an initial arrangement, include all the elements in the code and use the member function in Prolog) step-by-step. Finally let's print the Prolog code.

Prompt 2

Does this program have a bug? How to fix it?

Prompt 3 (Extraction Prompt)

The output given by this program is:
<output>
Hence the correct arrangement is:
Note: If the output is false, print False.

System Instructions:

Assume you are a constraint optimization expert and you need to model a constraint satisfaction problem in Prolog.

If printing the elements, constraints, objective function and plan use the format:

"ELEMENTS:
CONSTRAINTS:
OBJECTIVE FUNCTION:
PLAN:"
Do not use the write function from Prolog when you are coding in Prolog.

OpenAI Playground Example:

https://platform.openai.com/playground/p/0C76QEKY0Vl9f8uraA6BArQu?model=gpt-4&mode=chat