Learning Automata-Based Task Knowledge Representation from Large-Scale Generative Language Models

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Abstract

Automata-based representations play an important role in control and planning in sequential decision-making, but obtaining high-level task knowledge for building automata is often difficult. Although large-scale generative language models (GLMs) can help automatically distill task knowledge, the textual outputs from GLMs are not amenable for formal verification or use in sequential decision-making. We propose a novel algorithm named GLM2FSA, which obtains high-level task knowledge represented in a finite state automaton (FSA) from a given brief description of the task goal. GLM2FSA sends queries to a GLM for task knowledge in textual form and then builds a FSA to represent the textual knowledge. It fills the gap between text and automata-based representations, and the constructed FSA can be directly utilized in formal verification. We provide an algorithm for iteratively refining the queries to the GLM based on the outcomes, e.g., counterexamples, from verification. We demonstrate the algorithm on examples that range from everyday tasks, e.g., crossing a road and making coffee, to security applications to laboratory safety protocols.

Introduction

Automata-based representations of high-level task knowledge play a key role in planning and learning in sequential decision-making. Such knowledge may include the requirements a designer wants to enforce on an agent and a priori task information about the agent and the environment in which it operates. Automata-based representations are useful in many applications, such as lexical analysis of compilers (Brouwer, Gellerich, and Plödereder 1998; Arnaiz-González et al. 2018), reinforcement learning policy optimization (Zhang, Wang, and Gao 2021; Fang et al. 2020; Valkanis et al. 2020; Xu et al. 2020), and program verification (Vardi and Wolper 1986).

Despite their utility in a range of applications, capturing high-level task knowledge in automata is not straightforward. Automata learning algorithms infer such knowledge through queries to a human expert or an automated oracle (Narendra and Thathachar 1974). On the other hand, they may require an excessive number of queries to a human, and it is often unclear how an automated oracle can be constructed in the first place. Even in cases in which an oracle exists, either the learning algorithm or the oracle requires prior information, such as the set of possible actions available to the agent and environmental responses, i.e., symbols relevant for the automata construction. It is often unclear how to obtain this information. Furthermore, the soundness of the inferred automaton depends on the choice of symbols.

We argue—and provide a proof of concept—that recent advances in so-called large-scale generative language models (GLMs) can help automatically distill high-level task knowledge. Existing GLMs, such as Generative Pre-trained Transformer-3 (GPT-3) (Brown et al. 2020), are capable of generating realistic, human-like text in response to queries. Such text may, for example, encode rich world knowledge. On the other hand, the output of GLMs is typically in a textual form and may not be directly utilized for sequential decision-making or automata learning. Moreover, the textual form outputs are not formally verifiable, hence not capable of applications where correctness matters.

We develop an algorithm named GLM2FSA to fill the gap between the outputs from GLMs and automata-based rep-
resentations of high-level task knowledge. GLM2FSA produces high-level task knowledge represented in finite state automata (FSAs) from a brief task description—a phrase or a short sentence to describe the task (e.g., cross the road). Specifically, GLM2FSA first sends queries on the task description to GPT-3 to obtain a list of text instructions organized in steps (and substeps). Then, it parses the text instruction to define the input and output symbols (i.e., environment propositions and actions) of the FSA and interprets each step to construct a state and its outgoing transitions. GLM2FSA constructs FSAs which is utilisable for sequential decision-making and can be formally verified.

We illustrate an example in Figure 1 in which GLM2FSA constructs a FSA from a given task description “cross the road”. GLM2FSA first queries GPT-3 for the steps to achieve this task, then queries for subsequent substeps, and obtains a list of step descriptions in textual form for each (sub)step. It then applies semantic parsing to extract the verb phrases and predefined keywords from the step descriptions. The algorithm constructs one state to represent each step. The verb phrases and keywords from each step define the symbols and outgoing transitions of the state corresponding to this step. GLM2FSA outputs a FSA with the defined states, symbols, and transitions.

We empirically show that GLM2FSA is capable of constructing FSAs to represent task knowledge. Due to GPT-3’s wide range of knowledge domains, GLM2FSA can build FSAs for domain-specific tasks. We demonstrate the capability of the algorithm, from everyday tasks to security applications to laboratory protocols. We provide examples of constructing FSAs that represent all the details in the step descriptions and capture multiple solutions to a task. We also show examples of verifying the FSAs to indicate that we can check if the FSAs can accomplish the goal we set.

Furthermore, we propose a refinement procedure that enables further querying GPT-3 to refine the FSA based on the verification result. We show an example of querying GPT-3 for substeps and reconstructing the FSA once we detect the failure of verification. To our best knowledge, this is the first algorithm that constructs automata-based representations from natural language extracted from large-scale GLMs. GLM2FSA is also the first to provide an approach to verify the knowledge from GLMs and refine the FSAs based on the verification results.

Related Work

Extracting Task Knowledge from Language Models.

Prior works have tried to extract task knowledge from large language models [Xiong et al. 2019; Davison, Feldman, and Rush 2019; Petroni et al. 2019]. Due to the lack of rich world knowledge, the language model they use cannot generate action plans without providing detailed task descriptions. The recently introduced large text generative model—GPT-3 [Brown et al. 2020]—contains rich world knowledge and can generate instructions for a given task [Hendrycks et al. 2020]. Therefore, some works extract task knowledge by asking GPT-3 for the step-by-step instructions [West et al. 2021; Huang et al. 2022]. However, the task knowledge is in textual form, which is not directly utilisable by the control systems for sequential decision-making. We are the first to transform texts into automata-based representations utilisable and verifiable by control systems.

Symbolic Knowledge Representations.

Many works focus on constructing symbolic representations of task knowledge from natural language (text) descriptions. Some works [West et al. 2021; Rezaei and Reformat 2022; He et al. 2022] extract information from text descriptions of given tasks and construct knowledge graphs for the tasks. Another work [Lu et al. 2022] analyzes the causality within the text descriptions and creates causal graphs. In contrast with the existing works, we generate automata-based representations from the text descriptions. Automata-based representations are more useful in the fields such as formal method [Biggar and Zamani 2020; Vardi and Wolper 1986] and reinforcement learning [Cat et al. 2021a;b; Fang et al. 2020], which are sequential decision-making. The knowledge or causal graphs in the existing works are incapable of sequential decision-making and not verifiable.

Natural Language to Formal Language.

Several works [Vadera and Meziane 1994; Baral et al. 2011; Sadoun et al. 2013; Ghosh et al. 2014] introduce approaches to transform natural language to formal language specifications. A method in [Kate et al. 2005] induces transformation rules that map natural-language sentences into a formal query or command language. Those works stop at transforming formal language specifications without further applying them to sequential decision-making. Another work [Huang et al. 2022] constructs a form of actionable knowledge that machines can recognize and operate sequentially. However, this work cannot handle conditional transitions, e.g., multiple transitions from one state. We propose an algorithm for transforming natural language into finite state automata, which can handle conditional transitions in sequential decision-making.

Preliminary

Finite State Automata

A finite state automaton (FSA) is a tuple \( A = \langle \Sigma, A, Q, q_0, \delta, \sigma \rangle \) where \( \Sigma \) is the input alphabet (the set of input symbols), \( A \) is the output alphabet (the set of output symbols) or action set, \( q_0 \in Q \) is the initial state, \( F \subseteq Q \) is the set of final states, and \( \delta : Q \times \Sigma \times A \times Q \rightarrow \{0, 1\} \) is the transition function, which indicates that a transition exists when it evaluates to 1. Note that FSAs transitions are non-deterministic in our definition, such that if the current state is \( q_i \in Q \) and one sees \( \sigma \in \Sigma \), one can choose the action and next state among the set \( \delta(q_i, \sigma) = \{(a_i, q_j) \in A \times Q | \delta(q_i, \sigma, a_i, q_j) = 1\} \).

We use FSAs in the context of sequential decision-making, where the input alphabet is composed of all possible observations of the environment. We introduce the set of all (relevant) atomic propositions \( P \), such that \( \Sigma := 2^P \), i.e., an input symbol \( \sigma \in \Sigma \) is the set of atomic propositions that evaluates to True. We can define propositional logic formula based on these atomic propositions (for example, \( \varphi = \neg p \land q \) where \( p, q \in P \)). By extent, we say that
the transition \((q_i, \varphi, a, q_j)\) exists if for all \(\sigma \in \Sigma\) that satisfy \(\varphi\) we have \(\delta(q_i, \sigma, a, q_j) = 1\), i.e., if the current state is \(q_i\) and the condition \(\varphi\) holds, one can choose the transition with action \(a\) and next state \(q_j\).

When interpreting final states \(q_i \in F\) as states where the task is achieved while no more decisions are required. We also allow for a “no operation” action \(\epsilon \in \mathbb{A}\). Figure 2 depicts an example of FSA.

**Linear Temporal Logic**

Linear temporal logic (LTL) is a formal language used to express systems’ properties that evolve over time. It is built on top of propositional logic by extending it with temporal operators that allow reasoning about the system’s future behavior. We use LTL to define the specifications for verifying the FSA.

Define \(A\) and \(\Phi\) as LTL formulas. Formally, LTL formulas are defined inductively as

\[
\varphi := p \in P_M | \neg \varphi | \varphi \lor \varphi | \varphi \land \varphi | \varphi U \varphi
\]

• A set of atomic propositions, denoted by lowercase letters (e.g., car come), represent the system’s state.

• A set of temporal operators describes the system’s temporal behavior.

• A set of logical connectives, such as negation (\(\neg\)), conjunction (\(\land\)), and disjunction (\(\lor\)), that can be used to combine atomic propositions and temporal operators.

As syntax sugar, along with additional constants and operators used in propositional logic, we allow the standard temporal operators \(\diamond\) (“eventually”) and \(\square\) (“always”).

**Controller**

A controller refers to a system component responsible for making decisions and taking actions based on the system’s state. A controller can be mathematically represented as a mapping from the system’s current state to an action, which can be a control input or a setpoint. It is often represented as a FSA in a formal verification setting.

The controller’s goal is to adjust the control input so that the system’s state evolves in a way that satisfies certain performance criteria, such as stability, accuracy, and robustness. The criteria are often specified using formal languages, such as LTL.

This paper proposes an algorithm to construct a controller, represented as a FSA from GPT-3’s responses. The controller makes decisions and takes actions based on its current state to fulfill the task we provided.

**Generative Language Model**

A generative language model (GLM) produces human-like text completion from a given initial text (prompt). The produced texts continue filling the content from that prompt. Recent GLMs are deep learning models with millions or billions of parameters; hence they are called large-scale GLMs.

Generative Pre-trained Transformer 3 (GPT-3) is the current state-of-the-art large-scale GLM. It is pretrained by five large-scale datasets with over 5 billion words. GPT-3 offers four primary models with different capabilities for different tasks (Brown et al. 2020). Davinci-002 is the most capable model that can do question-answering, next-sentence prediction, and text insertion. We query Davinci-002 to obtain task instructions for empirical analysis.

GPT-3 allows users to customize settings by setting the hyper-parameters. For instance, max_tokens restricts the maximum number of tokens (words and punctuation) of the generated text, and temperature defines the randomness of the outputs. We propose an algorithm that specifies grammar rules for certain keywords. Hence we set bias on the keywords to ensure the model outputs them instead of their alternations. Setting bias to keywords eliminates the need to transform synonyms to the corresponding keywords or define new rules for those synonyms.

**Semantic Parsing**

Semantic parsing is a task in natural language processing (NLP) that converts a natural language utterance to a logical form: a machine-understandable representation. It applies to many NLP tasks, including machine translation, question answering, code generation, and automated reasoning.

There are many approaches to semantic parsing and different types of logical forms. We follow the approach that predicts part-of-speech (POS) tags for each token and builds phrase structure depending on phrase structure rules, also known as grammar. POS tags include noun (N), verb (V), adjective (AJD), adverb (ADV), etc. Phrase structure is a tree-structured logical form whose leaves are the POS tags of the given natural language utterance (i.e., sentence). Phrase structure rules organize the POS tags into phrases like noun phrases (NP) and verb phrases (VP).

Definition 1. A Noun Phrase (NP) is a group of words headed by a noun. A Verb Phrase (VP) is composed of a verb and its arguments. VP follows the following grammar:

\[
\text{VP} \leftarrow \text{V} \text{ VP} \\
\text{VP} \leftarrow \text{V} \text{ NP}
\]

The left-hand side of the grammar is composed of the components on the right-hand side. The grammar defines a verb phrase as either composed of a verb and another verb phrase or composed of a verb and a noun phrase.

To standardize the words under the phrase structure, the parsing approach we follow also converts all the words to their original form, e.g., removes singular or plural, removes past tense, etc. Such an operation eliminates cases where
phrases with the exact words but in different tenses are categorized into two distinct phrases.

### Methodology

We explain how the proposed algorithm, GLM2FSA, operates in this section. The algorithm starts from querying GPT-3 for the task knowledge in textual form and eventually constructs a controller, represented as a FSA, that can make decisions to fulfill the task.

### Extracting Textual Knowledge

The algorithm first extracts knowledge from GPT-3 with iterative queries. Given a task description of interest, the algorithm first asks for steps to achieve the task. We also provide a method to refine a step (or substep) into its substeps. We present here the template of a conversation with GPT-3 using the Davinci-002 model (prompts sent to GPT-3 in blue, completion of GPT-3 in red):

```plaintext
Steps for: task description

[1] step description

[step number] step description

[step number,1] step description

[step number,2] step description

... Substeps for: [step number] step description

[step number,1] substep description

[step number,2] substep description

... Note that the prompts for substeps include the history of previously queried steps (prompt and completion). Algorithm 1 depicts the iterative process of querying for steps and substeps until a predefined depth of substeps is reached. The user might define interactively which steps to refine into substeps instead of specifying a predefined depth.

Algorithm 1: Query from GPT-3 Language Model

1: procedure GLM2STEP(String TASK_NAME, integer DEPTH) ▷ Obtain the instructions for a given task; depth indicates how detailed the instructions are.
2:  PROMPT = “Steps for: “ + TASK_NAME + “\n [1]”
3:  ANSWER = GPT(PROMPT)
4:  STEP_NUMBERS = [“/1”], “/2”, “...”
5:  for i in range(1, DEPTH) do
6:    SUB_NUMBERS = [i]
7:    ANSWER = [i]
8:    for number in STEP_NUMBERS do
9:      SUB_PROMPT = “Substeps for “ + number
10:     ANSWER.append(GPT(SUB_PROMPT))
11:     SUB_NUMBERS.append([“/1”], “...”)
12:   end for
13:   STEP_NUMBERS = SUB_NUMBERS
14: end for
15: return STEPS = (STEP_NUMBERS, ANSWER)
16: end procedure

Building FSA from Texts

The step descriptions generated by GPT-3 are in textual form, which is not directly interpretable by the planning or learning algorithms in sequential decision-making. The algorithm GLM2FSA transforms step descriptions from textual form to finite state automata, which resolves the interpretation problem. We present the transformation procedure in Algorithm 2.

The algorithm first applies semantic parsing to each step description to obtain the keywords and verb phrases. The semantic parsing method classifies the part-of-speech tags of each word in a sentence and builds word dependencies based on grammar. The algorithm extracts the words whose part-of-speech tag is verb and the dependencies of those words; each verb with its dependency is a verb phrase. Then, the algorithm extracts pre-defined keywords in the sentence. We implement a parse function for the keyword and verb phrase extractions.

Then, the algorithm constructs a FSA from the steps and verb phrases within these steps. Recall that a step consists of a step number and a sentence of description. It transforms the steps and verb phrases into required components, including a finite set of states Q, a finite set of atomic propositions P, a finite action set A, a transition function δ, an initial state q0, and a set of final states F.

For each step, we add a state qi representing the current step i to Q. We define the state corresponding to the first step as the initial state and manually add a state done as the only final state. Then, we build sequential transitions between the states as the default transitions.

#### Default Transitions

We define default transitions as transitions from the current state to the next state with condition True. Each state qi only has one outgoing transition to its next state qi+1, with the verb phrases from the ith step as the output symbols. A default transition δ(qi, True, VPi, qj+1) exists, unconditionally of the valuation of the atomic propositions in P (hence the condition True). A demonstration of the default transition is presented in the first row of Table 1.

The verb phrases are interpreted as the condition and output symbols. We divide the verb phrases into two categories:

**Definition 2.** VP^A is a verb phrase that leads to actions, and VP^C is a verb phrase indicating the conditions for triggering the transitions.

VP^A always stands alone, as opposed to VP^C, which associates with pre-defined keywords such as ‘if’. By default, the algorithm considers a verb phrase as a VP^A unless the grammar of a keyword specifies that the verb phrase is VP^C. The algorithm adds VP^A to the set of output symbols A and VP^C to the set of atomic propositions P.

If a condition verb phrase VP^C includes a negation word ‘no’ or ‘not’ in the beginning:

\[ VP^C \leftarrow \neg VP_n^C \]

then instead of considering the verb phrase as a new condition verb phrase, the algorithm adds the condition verb phrase without the negation word (VP^C) to the set of atomic propositions P and considers the formula \(\neg VP^C\) as the condition of the corresponding transition.

Occasionally, the algorithm replaces the default transitions with special transitions defined by the grammar with the keywords. We select several keywords and define their
Algorithm 2: Natural Language to FSA

1: ```prolog
procedure STEP2FSA(List[String] STEPS, List[String] keywords, function keyword_handler)
```
2: ```prolog
Q = [a state for each step] + [done]
```
3: ```prolog
q₀, F = Q[0], {done}
```
4: ```prolog
P, A, δ = {}, {∅}, {∅}
```
5: ```prolog
for state_number in [0 : |Q| − 1] do
```
6: ```prolog
STEP_NUMBER = step number of the current state
```
7: ```prolog
VP_AND_KEYS = parse(STEPS[STEP_NUMBER])
```
8: ```prolog
if any(keywords) in VP_AND_KEYS then
```
9: ```prolog
keyword_handler(Q, VP_AND_KEYS, keywords)
```
10: ```prolog
else
```
11: ```prolog
create δ(qstate_number, True, VP_AND_KEYS, qstate_number+1)
```
12: ```prolog
A := A ∪ {VP_AND_KEYS}
```
13: ```prolog
end if
```
14: ```prolog
end for
```
15: ```prolog
return P, A, Q, q₀, F, δ
```
16: ```prolog
end procedure
```

We define a type of transition called the **keyword_handler**, which are implemented in the **keywords**. We consider the following three groups of transition rules:

**Direct State Transitions.** We define a transition from the current state \( q_i \) to a state other than the next state \( q_{i+1} \), called direct state transition. The direct state transition happens when there is a verb phrase in the step description consisting of a formally defined step number. The transition rule for direct state transition is presented in the second row of Table 1. Note that \( ← \) in Table 1 captures the dependencies, meaning that the \( VP^A \) is composed of another \( VP^A \) and a step number.

Once the algorithm detects a phrase in such a format, it builds a transition from the current state to the state representing step \( j \) without adding any output symbol (using the “no operation” action \( c \)). This transition is unconditional (the condition is \( T \) true).

**Conditional Transitions.** We define a type of transition named conditional transition, in which the transition only happens when certain conditions are satisfied. The condition of a conditional transition is a conjunction of one or more atomic propositions in \( P \). The conditional transition is caught by the keyword ‘if’. The transition rule for conditional transition is defined in the third row of Table 1.

The algorithm builds two transitions from each sentence with the above patterns. The first transition consists of a starting state \( q_i \), a conjunction of atomic propositions \( VP^C \), a target state \( q_j \), and a set of outputs \( VP^A \). The second transition is a self-transition at \( q_i \) with a condition \( ¬VP^C \). The second transition does not have any output.

If the \( VP^A \) does not lead to a direct state transition, the first transition ends at \( q_{i+1} \).

**Self-Transitions.** We define a type of transition called self-transition, whose starting and target states are identical. The algorithm builds two transitions: a self-transition whose starting and target states are both the current state and the other transition that goes out from the current state and leads to the next state. The algorithm triggers self-transition when observing a verb phrase containing the keywords ‘wait’, ‘after’, or ‘until’. The rules for building the two transitions are defined in the fourth row in Table 1.

**Empirical Demonstration**

We construct several sets of automata-based representations to verify the ability of GLM2FSA and show its capability for some complex tasks. We provide examples to show that GLM2FSA can create FSA (controllers) that are unambiguous and can represent all the required knowledge of given tasks. Furthermore, we indicate the applicability range of GLM2FSA and some potential limitations.

**Crossing Road Example: Sanity Check.** We start with the crossing road example to verify that the automata-based representations created by GLM2FSA can represent all the task knowledge, regardless of how many details are in the generated texts.

First, we apply the algorithm to construct a FSA for first-layer step descriptions of the task “crossing the road”. The first-layer step descriptions are obtained from the responses from a GPT-3 by only querying the brief task description. In most tasks, the first-layer step descriptions are sufficient. The queries and the responses from GPT-3 are as follows:

```
Steps for: Cross the road
1. Look both ways before crossing the road.
2. If there are no cars coming, proceed to cross the road.
3. If there are cars coming, wait for them to pass before crossing the road.
```

GLM2FSA constructs a FSA to represent these steps, and the FSA is shown in Figure 3. The constructed FSA successfully represents all the required knowledge—actions...
| Category                | Grammar                          | Transition Rule                  |
|------------------------|----------------------------------|----------------------------------|
| Default-Transition     | $\text{VP}^A$                    | $q_i \rightarrow (\text{True}, \text{VP}^A) q_{i+1}$ |
| Direct-Transition      | $\text{VP}^A \leftarrow \text{VP}^A [j]$ | $q_i \rightarrow (\text{True}, \epsilon) q_j$ |
| Conditional-Transition | (if) $\text{if VP}^C, \text{VP}^A$ | $q_i \rightarrow (\text{VP}^C, \text{VP}^A) q_j$ |
| Conditional-Transition | (if else) $\text{if VP}^C, \text{VP}^A_1, \text{if } \neg \text{VP}^C, \text{VP}^A_2$ | $q_i \rightarrow (\text{VP}^C, \text{VP}^A_1) q_j$ |
|                       |                                  | $q_i \rightarrow (\text{VP}^C, \text{VP}^A_2) q_k$ |
| Self-Transition        | $\text{VP}^A \leftarrow \text{wait} \text{VP}^C \text{VP}^A$ | $q_i \rightarrow (\text{VP}^C, \text{VP}^A) q_{i+1}$ |
|                       | $\text{VP}^A \leftarrow \text{after} \text{VP}^C$ | $q_i \rightarrow (\epsilon, \text{VP}^A) q_{i+1}$ |
|                       | $\text{VP}^A \leftarrow \text{VP}^A \text{until} \text{VP}^C$ | $q_i \rightarrow (\text{VP}^C, \epsilon) q_{i+1}$ |

Table 1: Transition rules defined for keywords under specific grammar.

and conditions—under both conditions. The steps are represented by states in the FSA and operated sequentially. Hence, the FSA is utilizable in sequential decision-making. The algorithm creates the set of atomic propositions $P = \{\text{car come, pass, turn green}\}$ and output symbols $A = \{\text{"look way", "cross road", } \epsilon\}$ from the extracted verb phrases. Figure 3 indicates that GLM2FSA is capable of building automata-based representations that are unambiguous and able to represent all knowledge in first-layer step descriptions.

We have verified that GLM2FSA is capable of first-layer step descriptions. Then, we expose the details of the first-layer steps and examine whether GLM2FSA can build a FSA to represent all the details.

In the previous example, the algorithm extracts first-layer steps from GPT-3 by only querying a brief task description. Then, we can ask the algorithm to continue querying the substeps of each step. The substep descriptions returned from GPT-3 are called second-layer step descriptions. The second-layer step descriptions include much more detail than the first-layer descriptions. We then apply the algorithm to obtain the second-layer description by querying GPT-3 the substeps of each step for the task “cross the road”.

We present the constructed FSA for the second-layer descriptions in Figure 4. The FSA successfully indicates all the details in the second-layer step descriptions and is exploitable in sequential decision-making. The FSA consists of states representing each substep, a set of atomic propositions $P = \{\text{car come, pass}\}$, output symbols $A = \{\text{"look way", "cross road", “face direction”, “look left”, “look right”, } \epsilon\}$, an initial state $q_{i1}$, and a final state $q_{i4}$. This example demonstrates the ability of GLM2FSA to construct FSAs that represents detailed descriptions.

However, there is a logical flaw in state $q_{22}$ and its outgoing transitions. State $q_{22}$ is the state after the cross-road action; hence its outgoing transition should lead to the final state. The FSA in Figure 4 continues the loop after state $q_{22}$ because it fully represents the descriptions from GPT-3.

This observation leads to a shortcoming of GLM2FSA, which is GLM2FSA exactly follows the step descriptions from GPT-3 to construct automata-based representations. Therefore, the algorithm may build a FSA that does not match the real-world settings when GPT-3 provides misleading step descriptions.

We present a way of verifying the textual descriptions generated by GPT-3 and an approach to address the logical flaw in the next section.
We have shown the capability of GLM2FSA to first-layer and second-layer descriptions. In this example, we explore integrating the descriptions from the two layers.

In practice, we do not need the details for all the steps generated by GPT-3. Some step descriptions are straightforward, and others may need further explanation. Therefore, we apply GLM2FSA to build a FSA that represents the first-layer and the second-layer step descriptions simultaneously.

First, we apply the algorithm to query GPT-3 and obtain the step and substep descriptions:

Phone Call Example: Partial Extension. We have shown the capability of GLM2FSA to first-layer and second-layer descriptions. In this example, we explore integrating the descriptions from the two layers.

In practice, we do not need the details for all the steps generated by GPT-3. Some step descriptions are straightforward, and others may need further explanation. Therefore, we apply GLM2FSA to build a FSA that represents the first-layer and the second-layer step descriptions simultaneously.

First, we apply the algorithm to query GPT-3 and obtain the step and substep descriptions:

Cooking Egg Example: Multi-Channel Representation. We showed that GLM2FSA could construct partially extensible automata-based representations, in which part of the states can be extended to represent more details. In this example, we will demonstrate that the algorithm can also be used to construct an automata-based representation representing multiple ways of doing a task.

To obtain the step descriptions in multiple ways, we first ask the algorithm to query GPT-3 on three ways of accomplishing the task. Then, we input three task descriptions describing the three ways into the algorithm separately. The algorithm queries for the steps of each way to GPT-3, recursively applying the algorithm to extend different states until we satisfy all the details represented in the FSA.
pointing to the initial states of the three FSAs, with different algorithms creating an initial state and three outgoing transitions separate FSAs to represent each approach. Then, the algorithm creates a list of step descriptions.

\[
\begin{align*}
q_1 & \xrightarrow{\text{q}_2} (\text{True}, \text{"dial number")}) \xrightarrow{\text{"press call button")}} q_4 \\
\text{start} & \xrightarrow{\text{q}_1} (\text{True}, \text{"find number")}) \xrightarrow{\text{"dial number")}} \text{q}_2 \\
\text{start} & \xrightarrow{\text{q}_1} (\text{True}, \text{"find number")}) \xrightarrow{\text{"dial number")}} \text{q}_2
\end{align*}
\]

(a) Without substeps.

(b) With substeps.

Figure 5: Automata-based representation for “making a phone call with a cellphone”. (a) shows the FSA of first-layer steps. (b) shows the FSA in which the step associated with q2 is extended to its substeps for more details.

spectively, to get three lists of step descriptions:

Three ways of "cooking an egg":
- Boiling
- Frying
- Scrambling

Steps for: boiling an egg
1. Fill water in a pot.
2. Place the egg in the pot.
3. Boil the water.
4. Remove the egg from the pot after it has cooked for 3-5 minutes.
5. Peel the egg.

Steps for: frying an egg
1. Heat oil in a frying pan over medium heat.
2. Add egg to the pan.
3. Cook until the whites are set.
4. Remove from the pan.

Steps for: scrambling an egg
1. Break an egg into a bowl.
2. Whisk the egg until the yolks and whites are combined.
3. Heat a pan over medium heat.
4. Add oil to the pan.
5. Add the egg to the pan.
6. Scramble the egg until it is cooked to your liking.

The conditions of the three approaches do not interfere with each other; hence we apply GLM2FSA to build three separate FSAs to represent each approach. Then, the algorithm creates an initial state and three outgoing transitions pointing to the initial states of the three FSAs with different conditions. Another self-loop at the initial state is created to capture the case where none of the three situations are satisfied. Simultaneously, it merges the final states to finish building the automata-based representation.

We present the FSA in Figure 6 and indicate that GLM2FSA can construct a FSA representing multiple approaches to a task with post-processing.

Domain-Specific Task

In addition to the daily-life tasks we presented above, we show that our GLM2FSA with GPT-3 can also adapt domain-specific tasks, which indicates its wide range of applications. We present two examples in this section, one in the field of computer security and the other in biology. Such examples expand the application of GLM2FSA to the specific fields where human expertise is previously required.

Secure Multi-Party Computation. The first example is the task of “secure multi-party computation”. Secure multi-party computation (MPC) is a technique that allows multiple parties to jointly compute a function on their private inputs without revealing anything about their inputs to each other, or to any other third party. The MPC is a specialized problem in computer security, which may not be well-known by people outside this field. We use this example to show the capability of our algorithm on solving specialized problems. We query GPT-3 and get responses as the following:

Steps for: secure multi-party computation
1. Define problem and inputs.
2. Secret sharing of inputs.
3. Compute secret shares.
4. Reconstruct the final result.
5. Output verification.
6. Decrypt the final result.

The first-layer steps are too brief to be understandable. Therefore, we also query for the substeps of some steps above:

Substeps for: [2] Secret sharing of inputs.
1.2.1. Generate random secret shares.
1.2.2. Securely store secret shares.

Substeps for: [3] Compute secret shares.
1.3.1. Encrypt secret share.
1.3.2. Distribute encrypted shares.
1.3.4. Broadcast result.

We combine the first-layer steps and some of the substeps in one FSA as what we did in the “phone call” example. The FSA is shown in Figure 6 where we indicate the first-layer steps and second-layer substeps in two colors.

Biosafety Laboratory. Another example is the task of “passing a biosafety laboratory test”. The biosafety laboratory (BSL) test examines if a technician is capable of doing biology or biomedical experiments. This is a specialized task in the biomedical field. We send a prompt to GPT-3 and get the following responses:
Verification and Refinement

We have so far demonstrated the construction of controllers. This section will indicate that the controllers are verifiable and adjustable based on the verification results. Generally, we do not have a formal method to verify responses directly from large-scale language models. Constructing the automata-based representation resolves the verification problem.

We apply model checking to verify if the controller can accomplish the goals we expected. Specifically, human users will build a model where the controller can be applied and define a set of specifications. We finish the construction if the controller applies to the model and satisfies all the specifications. Otherwise, we will send new queries to GPT-3 and refine the controller based on its responses. Figure 7 illustrates the model checking and refinement procedures.

Environmental Model

We define an environmental model as a deterministic finite automaton (DFA) \( \mathcal{M} \) with input alphabet \( \Sigma_M := 2^P \). Here, \( P = \Sigma \cup \mathbb{N} \cup \ldots \) (including eventually problem constants). Effectively, we can represent such DFA \( \mathcal{M} \) where every transition is labeled with a formula over these propositions \( P_M \). We provide examples of such models in Figures 10 and 12.

Steps for: passing a biosafety laboratory test
1. Understand the biosafety guidelines.
2. Complete necessary safety training.
3. Follow the laboratory’s SOPs (standard operating procedures).
4. Wear appropriate PPE (personal protective equipment).
5. Properly handle, store, and dispose of materials.

Then, we construct the FSA displayed in Figure 8 to represent how to pass a BSL test.

So far, we have shown five groups of examples to demonstrate the wide-range ability of GLM2FSA and indicate its potential, as well as some shortcomings. In summary, GLM2FSA is an algorithm that can fill the gap between natural language and automata-based representations but lacks the ability to verify the representations.
Model Checking

Each FSA in the Experiment section that is constructed by GLM2FSA is a controller C. To verify the controller C, we manually create a model M represented in a FSA. Given an assumption A and a specification Φ, both are linear temporal logic (LTL) formulas. Then we verify if the model M satisfies the specification Φ following the controller C under the assumption A:

\[ M \otimes C \models \Phi. \] (1)

Due to the existence of temperature (random seed), GPT-3 often generates different phrases for the same meaning. Hence each action may correspond to multiple verb phrase expressions. In case the model checking does not fail due to unable to recognize synonyms, we query GPT-3 to ask if the two verb phrases refer to the same action. For example,

1. Are the two actions "wait for the call to connect" and "wait for answer the call" same?
2. No, the two actions "wait for the call to connect" and "wait for answer the call" are not the same.
3. Are the two phrases "cross the road" and "walk across the road" refers to the same action?
4. Yes, the phrases "cross the road" and "walk across the road" refer to the same action of traversing a road, typically by foot. Both phrases mean to go from one side of the road to the other side.

The model checking can verify the correctness of the controller generated by the GPT-3. Moreover, if the controller and model cannot satisfy the specifications, we can refine the controller by modifying the query to GPT-3.

We show the verifications of the FSAs constructed in the previous section to demonstrate that the GLM2FSA algorithm can generate verifiable representations of knowledge.

GLM2FSA algorithm resolves the issue that the correctness of GLMs outputs are not verifiable.

We use the NuSMV model checker (Cimatti et al. 2002) with a manually designed model, assumptions, and specifications to verify the controller designed with GLM2FSA. We present an example of how the NuSMV model checker verifies the controller in the Appendix.

Crossing Road Example. In the “crossing road” example, we take the FSA presented in Figure 3 as the controller and verify its correctness. We verify that a model can safely cross the road where no traffic light exists if it follows the controller.

We present the model in Figure 10. We assume that there is no traffic light exist and always eventually no car will come. Under the assumptions, we can check if the specification is satisfied, i.e., if we can reach the goal state eventually. We say FSA in Figure 3 correctly represents task knowledge if the goal state of the model is reachable.

Phone Call Example. In this example, we build two models to verify the first-layer steps and second-layer steps, respectively.

We build the first model to verify the required steps and their order. We present the first model in Figure 11a with the assumption and specification. It attempts to check the correctness of the FSA in Figure 5a. The first model and the controller will satisfy the specification if and only if the controller returns all the required steps in the expected order.

The second model in 12b attempts to check the correctness of the second-layer substeps represented in the FSA in Figure 5b. Similar to the first model, the specification will be satisfied if and only if all the required actions are taken in order consecutively.

In this “phone call” example, we show that the first-layer and second-layer sub-steps are verifiable by the model-checking technique. On a broader scale, sub-steps in every layer are verifiable.

Cooking Egg Example. For the FSA presented in Figure 6, we present two models, the first model is for checking whether an egg is added regardless of the way of cooking it, and the second model is for checking the key steps of...
frying an egg. The models, assumptions, and specifications are presented in Figure 12a and 12b. The first model simply checks if the action “add an egg” is taken before reaching the final state of the controller. The second model checks the steps of frying an egg. It satisfies the specification if and only if the controller takes the required actions in the correct order. Note that the specification can be satisfied if the required actions are not taken consecutively.

In this example, we indicate that one can verify different components of the FSA based on the requirements or preferences. The model can be flexible for different purposes.

**Refinement**

The GLM2FSA algorithm allows querying substeps and constructing a corresponding FSA (controller). We first start from the FSA of the first-layer steps and define a model and specifications to verify the FSA. If the controller does not satisfy the specifications, we refine the FSA by sending new queries to GPT-3 and reapply Algorithm 2 to obtain a new FSA. Then, we verify the new FSA and hence form a refinement loop. This refinement loop will finish once all the specifications are satisfied.

At each refinement, we apply Algorithm 1 to query GPT-3 for the next-layer steps (DEPTH = DEPTH + 1). This gives the substeps for all the current-layer steps. Next, we construct the automata-based representations of the next-layer steps following Algorithm 2. We denote the state that represents each current-layer step as the parent state and the states that represent the parent state’s substeps are called the children states.

We keep extending substeps until all the specifications are satisfied or the maximum number of layers is reached. If we reach the max number of layers and can still not satisfy the specifications, then we consider such a task is not representable by FSA. If the specifications are satisfied, we can complete the controller construction. Additionally, it is possible that not all children states are necessary for satisfying specifications. Hence we can prune unnecessary states to simplify the controller. The pruning process is defined as the following:
• start from the deepest-layer steps and replace the first set of children states with their parent state,
• check if the controller still satisfies all the specifications,
• keep the controller as it is if the specifications are satisfied, otherwise add the children states back;
• continue steps above for all of the children states until reaching the final state.

Cross Road Example. We continue using the “cross-road” task to iterate the refinement procedure. Figure 13a shows a model that requires actions out of the controller’s action space. Hence the specification will never be fulfilled using the controller constructed from first-layer steps (Figure 13b). Therefore, we follow the refinement procedure to query for second-layer steps (substeps of the first-layer steps) and construct a new controller to represent the second-layer steps. The controller (FSA) is presented in Figure 13c.

Then, we remove the states following the pruning process stated above. Through the pruning process, we only keep the children states of \( q_1 \) and present the pruned controller in Figure 13c. The controller in Figure 13c satisfies the specification shown in Figure 13a. Therefore, the refinement procedure terminates, and we do not send further queries to GPT-3. This new controller also resolves the logical flaw raised in the experiment section because we have pruned the unnecessary steps.

Conclusion

This paper shows proof of concepts for constructing automata-based representations from GLM. We design an algorithm named GLM2FSA that queries the brief task description to a large-scale GLM and constructs an automata-based representation for the task knowledge extracted from the responses of the GLM. The algorithm is highly automated, requiring only a short task description to build machine-understandable representations. We provide examples to show the capability of GLM2FSA. We empirically demonstrate that the generated automata-based representations can accurately represent all the details of the task knowledge.

Limitations. A limitation of GLM2FSA is that it constructs automata-based representations relying on the responses of GLM. The current state-of-the-art GLM such as GPT-3, occasionally generates misleading step instructions. The model-checking procedure relies on humans to build models manually, and the human-constructed models may not be able to check the correctness of all the steps.

Future Directions. As a future direction, we can design an automated or minimal human-involved verification method to verify the automata-based representation generated by GLM2FSA. From another perspective, we can develop an algorithm that takes human-inputted natural language and generates a model to verify the controller.

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Verification using NuSMV

MODULE environment -------------------------------------------------------------
VAR
car_come: boolean; -- cars are coming
car_pass: boolean; -- all cars passed
turn_green: boolean; -- the pedestrian traffic light turned green
FROZENVAR
traffic_light: boolean; -- there is a pedestrian traffic light
MODULE actions -----------------------------------------------------------------
VAR
face_direction: boolean; -- face direction of crossing
look_left: boolean; -- look left for cars
look_right: boolean; -- look right for cars
look_way: boolean; -- look both ways for cars
cross: boolean; -- cross the road
DEFINE COUNT_ACTIONS := count(face_direction, look_left, look_right, cross, look_way);
DEFINE none := COUNT_ACTIONS = 0; -- true iff no action is taken
INVAR COUNT_ACTIONS <= 1; -- cannot take two actions at once
INIT none;
MODULE controller_fig4(env,act) ------------------------------------------------
VAR state: {0, 11,12, 21,22, 3};
INIT state=0; -- the initial state
DEFINE goal := state=3; -- the desired state
TRANS case
state=0 & next(!env.traffic_light) :
next(act.none & state=11);
state=0 & next(env.traffic_light)
: next(act.none & state=21);
(state=11)
: next(act.look_way & state=12);
state=12 & next(env.car_come & !env.car_pass)
: next(act.none & state=12);
state=12 & next(!env.car_come | env.car_pass)
: next(act.cross & state=3);
(state=21)
: next(act.look_way & state=22);
state=22 & next(!env.turn_green)
: next(act.none & state=12);
state=22 & next(env.turn_green)
: next(act.cross & state=3);
goal
: next(act.none & goal);
 esac;
MODULE controller_fig5(env,act) ------------------------------------------------
VAR state: {11,12,13,14, 21,22,23, 31,32, 4};
INIT state=11; -- the initial state
DEFINE goal := state=4; -- the desired state
TRANS
  case
    state=11 :
      next(act.face_direction & state=12);
    state=12 :
      next(act.look_left & state=13);
    state=13 :
      next(act.look_right & state=14);
    state=14 & next(!env.car_come) :
      next(act.none & state=21);
    state=14 & next(env.car_come) :
      next(act.none & state=31);
    state=21 :
      next(act.cross & state=22);
    state=22 :
      next(act.look_way & state=23);
    state=23 & next(!env.car_come) :
      next(act.none & state=4);
    state=23 & next(env.car_come) :
      next(act.none & state=11);
    state=31 & next(!env.car_pass) :
      next(act.none & state=31);
    state=31 & next(env.car_pass) :
      next(act.none & state=32);
    state=32 :
      next(act.none & state=21);
    state=4 :
      next(act.none & state=4);
    esac;

MODULE model(env,act) ----------------------------------------------------------

VAR state: {
    q_init,q_sink,q_goal
};

INIT -- the initial state
  state=q_init;

DEFINE goal := -- the desired state
  state=q_goal;

TRANS
  case
    state=q_init & next(!act.cross) :
      next(state=q_init);
    state=q_init & next(act.cross & env.car_come) :
      next(state=q_sink);
    state=q_init & next(act.cross & !env.car_come) :
      next(state=q_goal);
    state=q_sink :
      next(state=q_sink);
    state=q_goal :
      next(state=q_goal);
    esac;

MODULE main --------------------------------------------------------------------

VAR env: environment;
VAR act: actions;

VAR controller: controller_fig4(env,act);
  -- VAR controller: controller_fig5(env,act);
VAR model: model(env,act);

LTLSPEC NAME assume_guarantee :=
  ( TRUE -- ASSUMPTIONS
    -- the flow of cars is not continuous
    & (G F !env.car_come)
    -- cars coming eventually passes
    & (G (env.car_come -> F env.car_pass))
    -- if all cars passed,
    -- then none are coming towards the crossing
    & (G (env.car_pass -> !env.car_come))
    -- -- if all cars passed,
-- -- then none are coming towards the crossing for a bit
-- & (G (env.car_pass -> G[0,2] !env.car_come))
-- -- if one has looked left and right recently and no car is coming,
-- -- no car will be coming for a bit
-- & (G |
-- (!env.car_come & (O[0,2] act.look_left) & (O[0,2] act.look_right))
-- -> (G[0,1] !env.car_come)
-- })
-- when pedestrian light is green, no car can come on the crossing
& (G ((env.traffic_light & env.turn_green) -> (!env.car_come)))
-- the model terminal state is eventually reached
& (F model.goal)
-- eventually, the controller rightfully thinks it achieved its goal
& (F (model.goal & controller.goal))
);