Security Policy Generation for Cloud-Based Security Services using Large Language Model

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***Abstract*—This project presents an AI-driven solution to automate security policy generation using the GPT-4o-mini language model. It focuses on translating natural language descriptions into XML policies compliant with the I2NSF Consumer-Facing Interface. The system simplifies the creation of policies for non-technical users, enabling seamless configuration of network security rules. By leveraging OpenAI's API, the model interprets user input and outputs structured, machine-readable policies aligned with IETF standards. The project demonstrates the feasibility of integrating large language models into cybersecurity workflows and highlights opportunities to improve scalability, context awareness, and interoperability within network security frameworks.**

***Index Terms*—Large Language Models (LLMs), I2NSF (Interface to Network Security Functions), Consumer-Facing Interface, Security Policy Automation.**

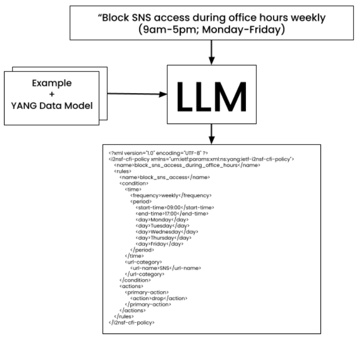
I. Introduction

Defining and enforcing security policies is a fundamental aspect of modern cybersecurity. These policies govern how network traffic is managed to ensure compliance with security standards and protect sensitive data. However, creating accurate, machine-readable policies often requires technical expertise, making it challenging for non-expert users.

The Interface to Network Security Functions (I2NSF) [1], developed by the Internet Engineering Task Force (IETF), provides a standardized framework for defining these policies. Its Consumer-Facing Interface specifies an XML schema for policy representation, ensuring consistency and interoperability. Despite its advantages, the manual creation of such policies is time-consuming and prone to errors.

This project addresses these challenges by leveraging GPT-4o-mini [2], a large language model optimized for structured data generation, and the powerful technique of prompting. By carefully designing prompts, the system can translate natural language descriptions into I2NSF [1]-compliant XML policies, more specifically into the Consumer-Facing Interface [3] XML policies. Prompting enables the model to effectively interpret user intent and generate highly accurate outputs, demonstrating the advantages of this approach for structured data tasks.

This work highlights the potential of prompting as a tool for bridging the gap between human intent and machine-executable configurations, making policy creation more accessible, efficient, and reliable.


"Block SNS access during office hours weekly (9am-5pm; Monday-Friday)
Example + YANG Data Model
LLM

```
<?xml version="1.0" encoding="UTF-8" ?>
<i2nsf-cfi-policy xmlns="urn:ietf:params:xml:ns:yang:ietf-i2nsf-cfi-policy">
  <name>block_sns_access_during_office_hours</name>
  <rules>
    <name>block_sns_access</name>
    <condition>
      <time>
        <frequency>weekly</frequency>
        <period>
          <start-time>09:00</start-time>
          <end-time>17:00</end-time>
          <day>Monday</day>
          <day>Tuesday</day>
          <day>Wednesday</day>
          <day>Thursday</day>
          <day>Friday</day>
        </period>
      </time>
      <url-category>
        <url-name>SNS</url-name>
      </url-category>
    </condition>
    <actions>
      <primary-action>
        <action>drop</action>
      </primary-action>
    </actions>
  </rules>
</i2nsf-cfi-policy>
```

Fig. 1. Diagram of the implemented system.

The remainder of this report is organized as follows. Section II provides context related to this work in security policy automation and language model applications. Section III outlines the methodology used in designing our system to generate I2NSF [1] security policies. Section IV presents the implementation details and the obtained results. Finally, Section VI concludes the report with a summary of the findings and potential directions for future work.

II. Context

First of all, it is essential to briefly explain the Consumer-Facing Interface [3]. The Consumer-Facing Interface (CFI) in the I2NSF framework allows security administrators to define high-level security policies that are subsequently translated into low-level configurations for enforcement by Network Security Functions (NSFs). Using an Event-Condition-Action (ECA) policy model, the CFI structures policies around specific events (e.g., system alarms), conditions (e.g., network traffic attributes or time-based restrictions), and actions (e.g., allowing, dropping, or rate-limiting traffic). The CFI also supports the definition of Endpoint Groups, which group network entities such as users, devices, and locations, simplifying the application of the policy. Integration with threat prevention allows for dynamic updates based on external risk data. The CFI's YANG data model ensures a standardized, machine-readable approach for defining and translating policies, facilitating seamless communication between users and security systems, and reducing the complexity of security policy management.

III. Methodology

The core of this project's methodology lies in the effective understanding of natural language descriptions and the careful design of prompts to translate these inputs into machine-readable structured XML policies compliant with I2NSF [1].

A. Natural Language Understanding

The system employs GPT-4o-mini [2], a language model optimized for structured data tasks, to interpret and process user input. This step is critical to bridge the gap between human-readable descriptions and machine-executable configurations.

The model is designed to extract the user's intent from natural language descriptions, identifying key components such as events, conditions, and actions. Conditions may include factors like specific time periods, days of the week, or URL categories, while actions involve tasks like allowing or blocking particular types of network traffic. This ensures that the system captures both the "what" (actions to be taken) and the "when" (conditions under which the actions should apply). Using GPT-4o-mini's advanced contextual understanding, the system accurately dissects complex policy descriptions.

B. Prompt Engineering

Prompting [4] is the cornerstone of this system, as carefully crafted prompts allow the model to generate the desired output without the need of fine-tuning it and consequentially, without a large amount of data. In this case, the prompt is designed to guide the model's attention to relevant details such as time constraints, URL categories, and actions, thereby ensuring compliance with the I2NSF [1] schema. The structure of the prompt is intentionally designed to detect and get specific elements of the security policy from the user's input.

1) Prompt Selector: To further enhance the functionality of the prompting mechanism, we implemented a prompt-selector system. This mechanism leverages the *LangChain* [5] framework to dynamically integrate few-shot examples to improve the performance of the large language model. Below, we detail the core components and their functionality within the prompt-selector mechanism:

An essential element of this mechanism is the *PromptTemplate*, which ensures that prompts maintain a consistent format. The defined template uses the following structure:

```
Question: {input}
{output}
```

This template serves to pair natural language inputs with corresponding structured outputs, enabling seamless interaction with the language model. Predefined examples are provided as a key input to the system. Each example consists of the following:

- **Input**: A natural language query, such as *"Restrict access to adult content from all devices."*
- **Output**: A structured XML response detailing the required policy, adhering to a specific schema. For instance:

```
<i2nsf-cfi-policy
    xmlns="urn:ietf:params:xml:ns:yang:ietf-i2nsf-cfi-policy">
    <name>restrict_adult_content_policy</name>
    <rules>
        <name>restrict_adult</name>
        <condition>
            <url-condition>
                <url-name>adult_content</url-name>
            </url-condition>
        </condition>
        <actions>
            <primary-action>
                <action>drop</action>
            </primary-action>
        </actions>
    </rules>
</i2nsf-cfi-policy>
```

The mechanism employs a *SemanticSimilarityExampleSelector*, which uses techniques such as vector embeddings to measure semantic similarity [6] between the user's query and predefined examples. Semantic similarity evaluates how closely the meanings of two pieces of text align, even if the wording differs. By converting text into numerical representations (embeddings) in a high-dimensional space, the selector calculates the proximity between the query and predefined examples, identifying those most relevant to the query's intent. This ensures the selection of the most contextually relevant examples for the task. These examples are then integrated into a cohesive prompt using a *FewShotPromptTemplate*, enhancing the model's task-specific understanding. The enriched prompt is processed by the language model to generate outputs, often in XML, which can be validated against schemas or business rules for domain alignment.

IV. Implementation

This section describes the design process of the prompt and showcases a generated CFI [3] policy security example. The general overview of the implementation is shown in Figure1. The code of our implementation can be found in the project's GitHub[1] repository and a brief video clip [2] explains the usage of the script.

When calling the model to translate the input into security policy XML format, we designed a specific prompt to condition the model. This prompt, in addition to making use of few-shot learning [7] providing the model with some examples of the objective task, it includes a detailed YANG data model of the Consumer-Facing Interface to serve as a guideline for the model.

After defining the prompt, we generated some examples with different inputs to test the performance of the model. Due to a lack of security policies, a quantitative evaluation of the implementation was not possible. Therefore, we evaluated the generated output taking into account its format, syntax and contents.

[1]https://github.com/jaehoonpauljeong/Data-Modeling-Group-2-Project
[2]https://youtu.be/yrNMPQB2R64

```
<?xml version="1.0" encoding="UTF-8" ?>
<i2nsf-cfi-policy
    xmlns="urn:ietf:params:xml:ns:yang:ietf-i2nsf-cfi-policy">
    <name>block_sns_access_during_office_hours</name>
    <rules>
        <name>block_sns_access</name>
        <condition>
            <time>
                <frequency>weekly</frequency>
                <period>
                    <start-time>09:00</start-time>
                    <end-time>17:00</end-time>
                    <day>Monday</day>
                    <day>Tuesday</day>
                    <day>Wednesday</day>
                    <day>Thursday</day>
                    <day>Friday</day>
                </period>
            </time>
            <url-category>
                <url-name>SNS</url-name>
            </url-category>
        </condition>
        <actions>
            <primary-action>
                <action>drop</action>
            </primary-action>
        </actions>
    </rules>
</i2nsf-cfi-policy>
```

Listing 1. Input: "Block SNS access during office hours with a weekly frequency (9am-5pm; Monday-Friday)"

For the provided example, we used the following input: *Block SNS access during office hours with a weekly frequency (9am-5pm; Monday-Friday)*. As shown in Listing1, the result looks promising. The format of the XML scheme follows the provided guidelines, the syntax is appropriate and overall it captured the required contents to construct the policy from the input text accordingly.

V. Execution Flow

The generation of XML policies follows 6 main steps.

1) **Define Examples with Input-Output Pairs:** Create a list of examples where each example consists of:
    - An *Input* in natural language, such as "Block malicious websites for my son's computer."
    - An *Output* in the form of a corresponding XML security policy.

    These examples serve as references for generating new outputs.
2) **Initialize Semantic Similarity Example Selector:** Use an embedding model to convert all example inputs into numerical vector embeddings. These embeddings are stored in a vector database, allowing the system to efficiently retrieve examples most relevant to a given query.
3) **Create Few-Shot Prompt Template:** Construct a prompt that combines the following components:
    - *Contextual instructions*: High-level guidance for generating XML security policies.
    - *Selected examples*: Examples retrieved based on their semantic similarity to the query, retrieved using semantic search algorithms.
    - *User input query*: The specific natural language query, input in high-level language, requiring an XML policy.
4) **Configure the Language Model (LLM):** Pass the constructed prompt to a language model, such as GPT-4. The model processes the input and generates the corresponding XML security policy.
5) **Process New Queries:** For a new input query:
    a) Search the vector database for semantically similar examples.
    b) Integrate the retrieved examples into the few-shot prompt template.
    c) Pass the final prompt to the LLM for output generation.
6) **Output:** Return the generated XML security policy as the final result.

VI. Conclusion

In conclusion, this project demonstrates the potential of large language models to automate the generation of I2NSF security policies from natural language descriptions. By using prompt engineering and the structured YANG data model of the Consumer-Facing Interface, the system simplifies policy creation for non-technical users, ensuring efficiency and compliance with standardized protocols. While qualitative evaluation shows promising results in terms of format and content alignment, future work should focus on expanding policy datasets for quantitative assessment, improving model scalability, and enhancing context awareness to address diverse cybersecurity scenarios. Moreover, the integration of our implementation with the I2NSF system should be considered after more research.

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