Result Summary - IAM Policy Classification Engine

Engine Description

I built a Python-based AI classification engine for analysing IAM policies.

The engine uses the OpenAI gpt-3.5-turbo model to review JSON-formatted IAM policies and classify them as either "Weak" or "Strong", based on cloud security practices.

Here's how it works:

- It loads the IAM policy from an input JSON file.
- Then, it sends the policy to GPT using a prompt I carefully designed to guide the model toward accurate and structured output.
- Finally, it saves the classification result and the reasoning into a new structured JSON file.

Part 1 – Refining Prompts

For Exmaple1 and Example2, I used the following prompt:

```
prompt = f"""
Classify the following IAM policy as either "Weak" or "Strong".

Respond using this JSON format:
{{
    "policy": <copy of the input IAM policy>,
    "classification": "Weak" or "Strong",
    "reason": "Short explanation."
}}

IAM Policy:
{json.dumps(policy_json, indent=2)}
"""
```

Example1 – Strong Policy:

Input JSON Policy:

Al output:

Example2- Weak Policy:

Input JSON Policy:

Al Output:

For Example3 and Example4, I used the following refined prompt:

```
prompt = f"""
You are a cloud security researcher. Your task
is to classify the
following IAM policy as either "Weak" or "Strong".
Return the result in exactly the following JSON format:

{{
     "policy": <copy of the input IAM policy>,
     "classification": "Weak" or "Strong",
     "reason": "Short explanation that clearly justifies the classification."
}}

IAM Policy:
{json.dumps(policy_json, indent=2)}

Make sure the 'reason' is written in full sentences and follows
best security practices (e.g., scope, least privilege, MFA, etc.).
"""
```

Example 3: Strong Policy

Input JSON Policy

Al output

```
"policy": {
    "Version": "2022-10-17",
    "Statement": [
        "Effect": "Allow",
"Action": "s3:DeleteObject",
        "Resource": "arn:aws:s3:::secure-bucket/*",
        "Condition": {
          "Bool": {
            "aws:MultiFactorAuthPresent": "true"
  "classification": "Strong",
  "reason": "This IAM policy is classified as 'Strong' because
it follows the principle of least privilege by only allowing
the specific action 's3:DeleteObject' on the specified resource
'arn:aws:s3:::secure-bucket/*'. Additionally, it includes a
condition that requires Multi-Factor Authentication (MFA) to be
present, adding an extra layer of security to the access
control. This policy ensures that only users with MFA enabled
can delete objects from the 'secure-bucket', enhancing the
overall security posture."
```

Example 4 - Weak Policy:

Input JSON Policy:

Al Output:

```
"policy": {
    "Version": "2022-10-17",
    "Statement": [
        "Effect": "Allow",
        "Action": "*"
        "Resource": "*"
  "classification": "Weak",
  "reason": "This IAM policy is classified as weak
because it grants unrestricted access to all
actions on all resources. This violates the
principle of least privilege, as it allows any
entity associated with this policy to perform any
action on any resource within the account. A
strong IAM policy should follow the principle of
least privilege by explicitly defining the actions
and resources that are allowed, limiting access to
only what is necessary for the entity to perform
its intended function."
```

Conclusion

Through the testing process, I noticed that the refined prompt gave much better results. The explanations were clearer, more professional, and reflected important best practices like least privilege, MFA, and scoping access.

Part 2 - Identify patterns where AI misclassifies policies

While working on the AI-based IAM classification engine, I observed that large language models (LLMs) like GPT can occasionally misclassify policies or return incomplete or generic explanations. These errors typically fall into a few well-defined patterns:

1. Overemphasis on Positive Indicators

Sometimes, the model focuses too much on the presence of a best practice (e.g., MFA), and ignores the fact that the policy still grants overly broad access (e.g., "Action": "*" and "Resource": "*"). This may lead to a false "Strong" classification, even though the policy is inherently insecure.

2. Misinterpretation of Complex Structures

LLMs can struggle with less common IAM features like NotAction, multiple statements in a single policy, or nested conditions. For example:

- A policy with NotAction may be mistakenly seen as restrictive when it allows almost everything.
- A policy with both a secure and insecure statement might be judged only by the more restrictive one.

3. Weak or Vague Explanations

Even when the classification is correct, the reason may lack depth:

Explanations like "This allows too many things" or "It's safe" don't reference best practices or provide clear justification. This reduces the trustworthiness and usefulness of the AI output.

Adjusting the Model Behaviour

To improve accuracy and consistency, I refined the prompt using the following strategies:

- clear definitions: I clearly told the model it is a <u>cloud security researcher</u>.
- Explicit format enforcement: I required the output to be a specific JSON structure and nothing else.
- **Inclusion of best practices**: I listed key principles the model should consider in its reasoning such as:
 - Limiting actions
 - Scoping access to specific resources
 - Requiring Multi-Factor Authentication (MFA)

Example

Although the policy includes MFA, it allows unrestricted access to all actions and resources, which violates the principle of least privilege.

GPT classified this as "Strong" due to the presence of MFA, while the policy is risky. here is what I got in the output file:

```
prompt = f""
  3. Respond strictly in the following JSON format (and nothing else):
   "classification": "Weak" or "Strong",
    "reason": "Clear and concise justification in 1-2 lines."
  {json.dumps(policy_json, indent=2)}
    - limiting actions,
    - scoping access to specific resources,
   - requiring Multi-Factor Authentication (MFA).
  - Do not include anything outside the JSON response.
I got this result:
     "policy": {
         "Version": "2022-10-17",
         "Statement": [
```

Conclusion

LLMs like GPT can be powerful tools for analysing IAM policies, but prompt quality directly determines output quality.

By identifying misclassification patterns and refining the instructions accordingly, I was able to significantly improve the precision, clarity, and professionalism of the Al's responses.

Part 3 - Test Multiple LLMs and Compare Responses

In this section, I compare the outputs of two different LLMs — OpenAI (GPT-3.5-Turbo) and Hugging Face(flant5-xl) — to analyse how each model classifies the same IAM policy and explains its reasoning.

The goal is to understand:

- How consistent each model is in its classification
- Whether the explanation includes key security best practices (e.g., scoping, least privilege, MFA)
- Which model gives more structured, clear, and helpful output
- And how sensitive each model is to weaknesses or edge cases in the policy

This comparison helps me evaluate the reliability and quality of each model's response when used in an AI-based classification engine.

For this policy:

```
prompt = f"""
You are a cloud security expert.

Classify the following IAM policy as either
"Weak" or "Strong" and explain why.

Respond in this JSON format:
{{
    "policy": <copy of the input policy>,
    "classification": "...",
    "reason": "..."
}}

IAM Policy:
{json.dumps(policy_json, indent=2)}
"""
```

This is the results I got:

OpenAI Result:

Hugging Face Result:

Conclusion

When I tested the OpenAI model (gpt-3.5-turbo), it gave me a well-structured JSON response with a clear explanation that included best practices like MFA and least privilege. The output was consistent, understandable, and matched exactly what I asked for — both in format and content.

But with Hugging Face (flan-t5-xl), the model only returned "Strong" as plain text, without any explanation and without following the required JSON format. Even if the classification was technically correct, the answer wasn't useful because it didn't include the reasoning or structure I needed. This shows that FLAN is not reliable when the task needs specific formatting or a deeper explanation.