

# UNIVERSITY OF TWENTE.



## Detecting Anomalous Misconfigurations in AWS Identity and Access Management Policies

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# Misconfigurations

## **Capital One Attacker Exploited Misconfigured AWS Databases**

After bragging in underground forums, the woman who stole 100 million credit applications from Capital One has been found guilty.

# Misconfigurations

## Capital One Attacker Exploited Miscon

After bragging in  
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## Three million senior citizens' info exposed by SeniorAdvisor

A security breach at SeniorAdvisor, a review website, compromised over three million elderly adults' personal information in August. [WizCase researchers](#) observed that a misconfigured Amazon S3 bucket exposed details including individuals' names, numbers, and email addresses. The information pertained to

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17 JUN 2021 NEWS

Amazon Web Services Misconfiguration Exposes Half a Million Cosmetics Customers

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## May 2022: 23 Million Files Exposed in Pegasus Airlines Breach

In May 2022, a [security firm discovered](#) an unprotected AWS S3 bucket containing 6.5 terabytes of “Electronic Flight Bag” information, including navigation information, proprietary software, and personal information pertaining to Pegasus Airlines crew members. Once notified of the exposed information, Pegasus Airlines promptly secured the unprotected S3 bucket.

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## July 2021: PeopleGIS Exposes Sensitive Data for Over 80 Municipalities

In July 2021, a group of ethical hackers at [WizCase](#) discovered a vulnerability affecting at least 80 municipalities in the United States. This breach resulted from misconfigured Amazon S3 buckets related to MapsOnline, a service run by the software company PeopleGIS. It's unclear whether the misconfiguration was made by PeopleGIS or by the municipalities in question.



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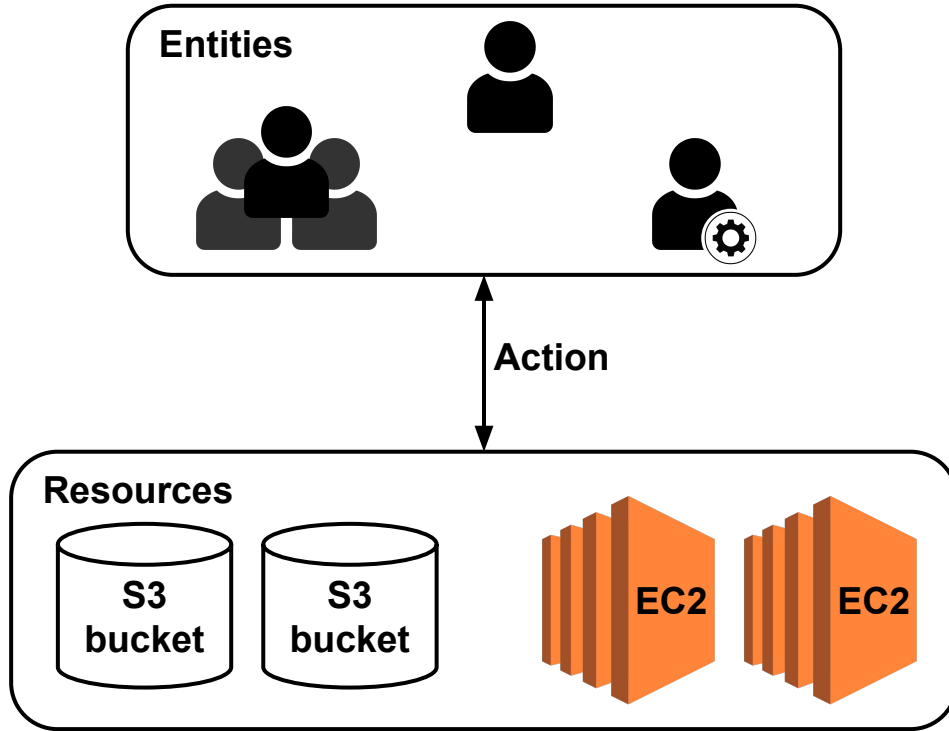
Misconfigured cloud  
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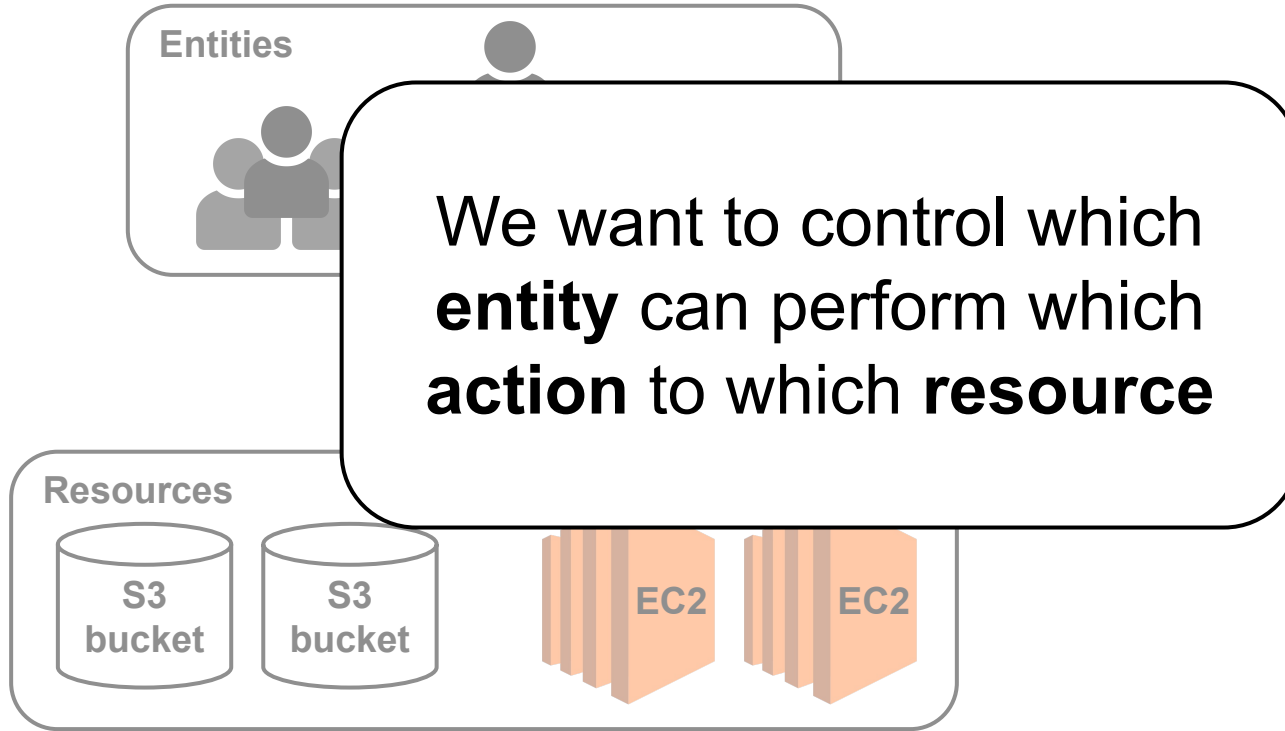
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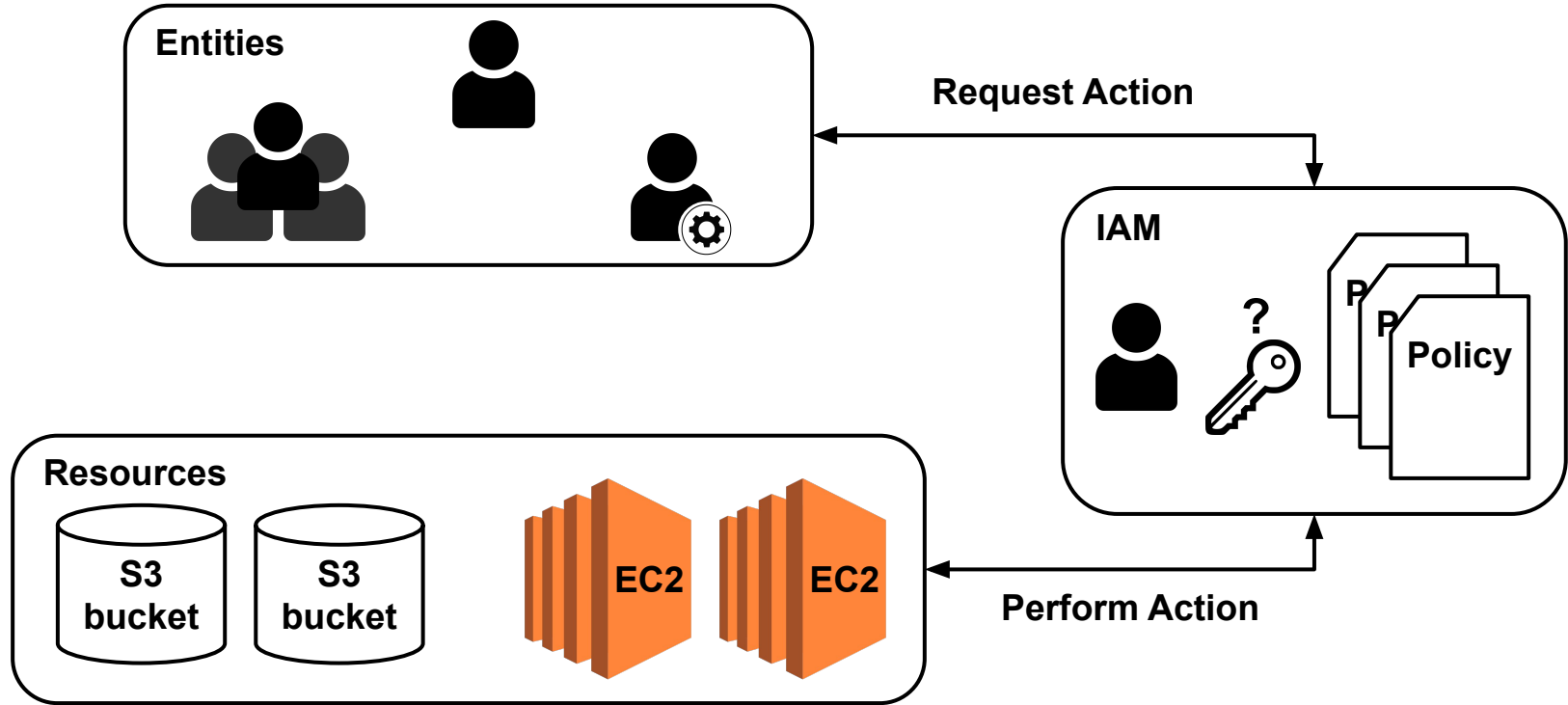




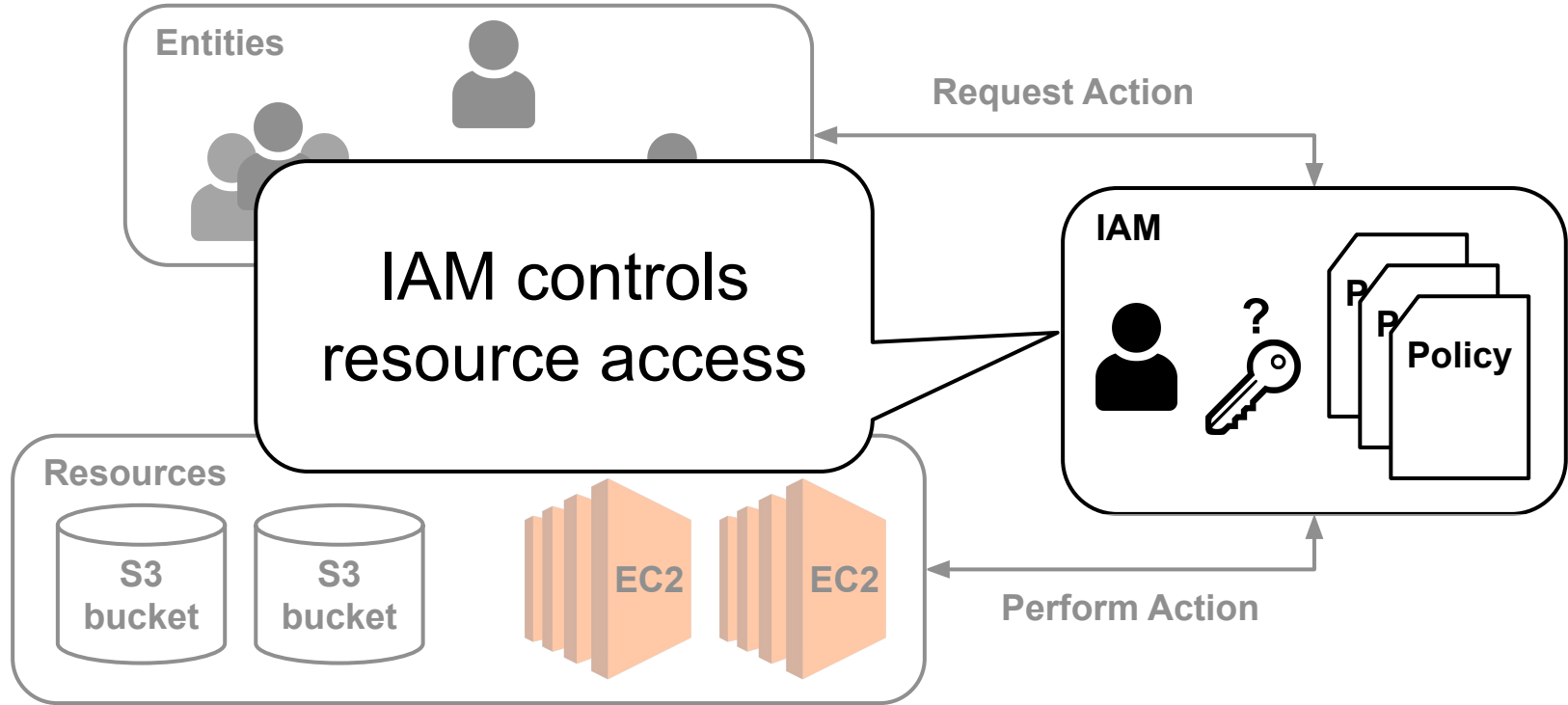
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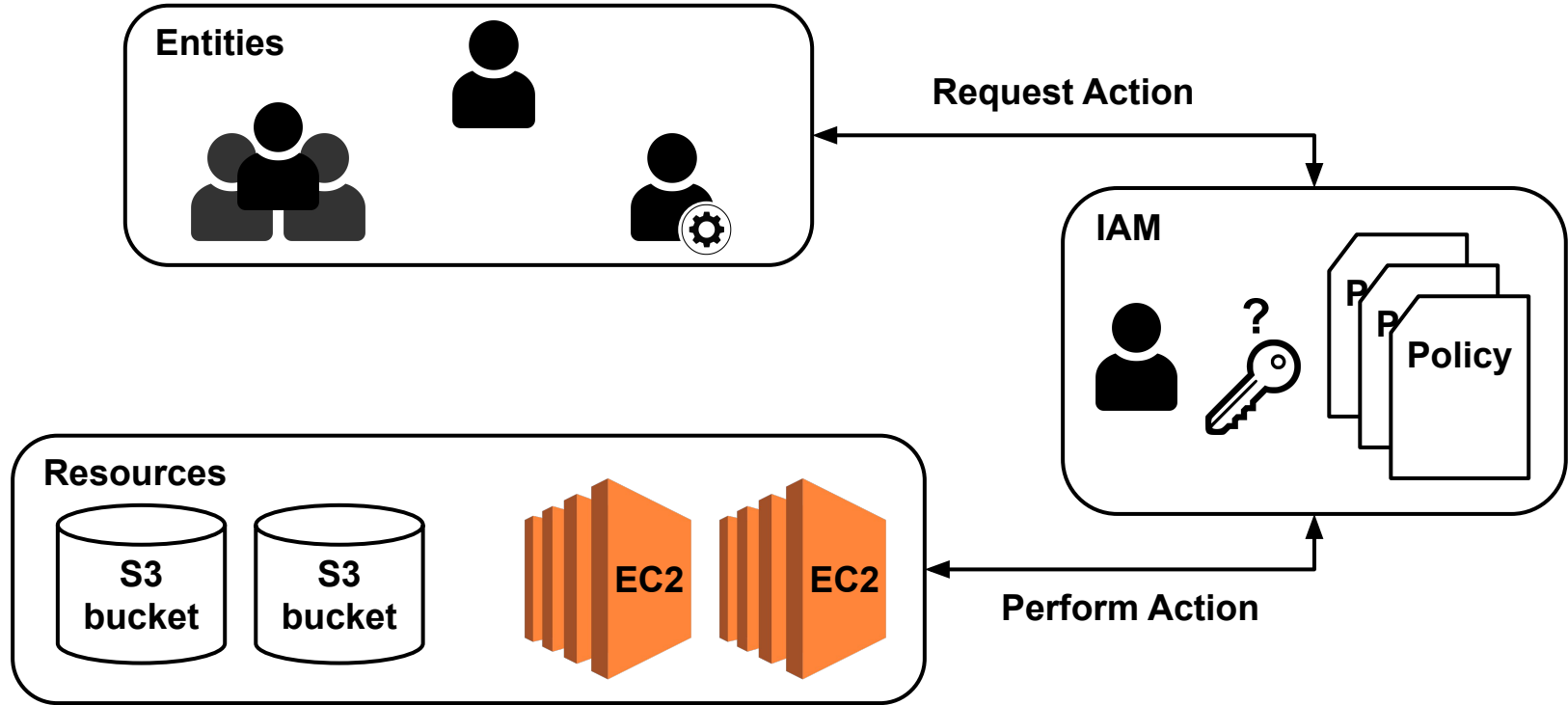
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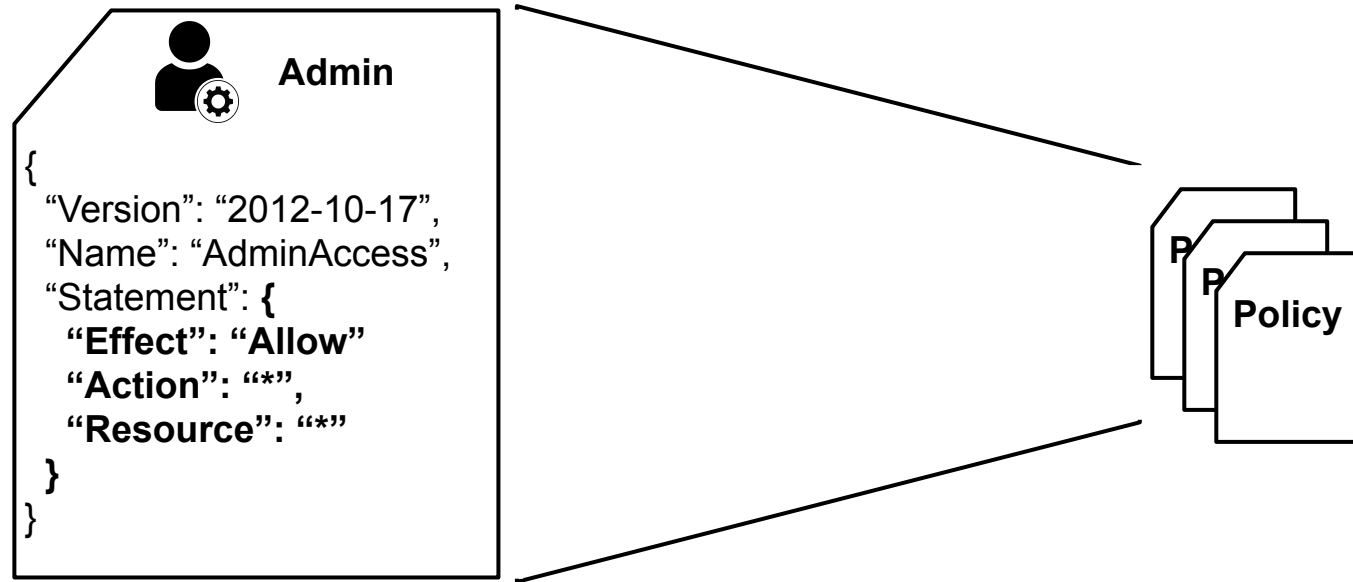
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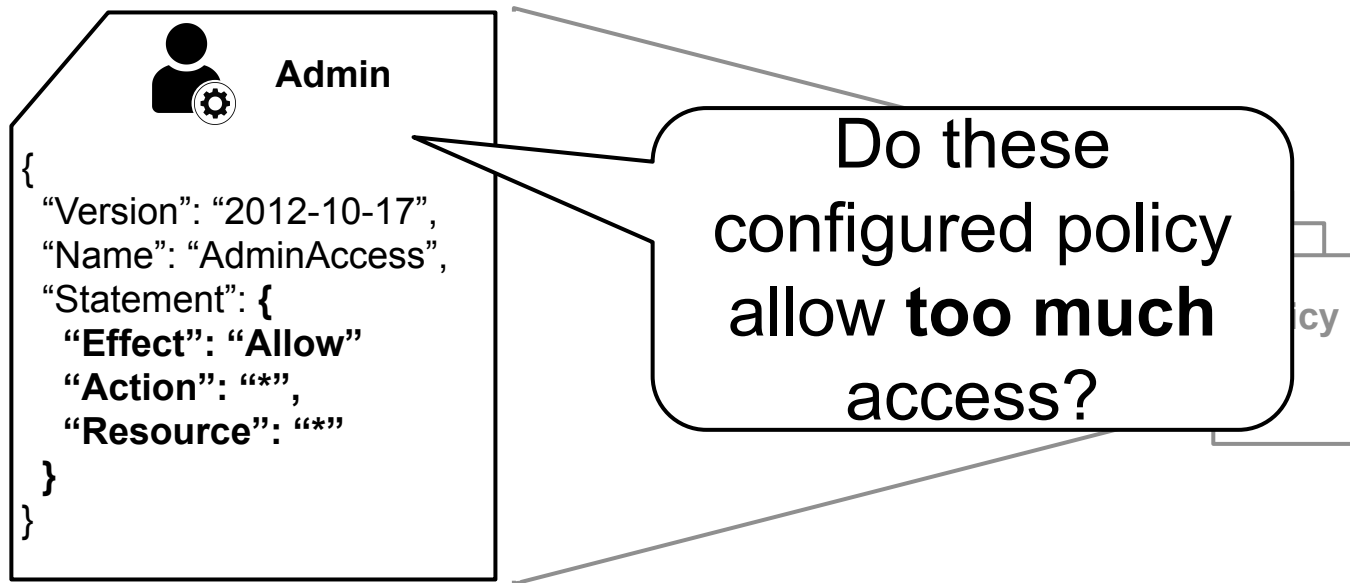
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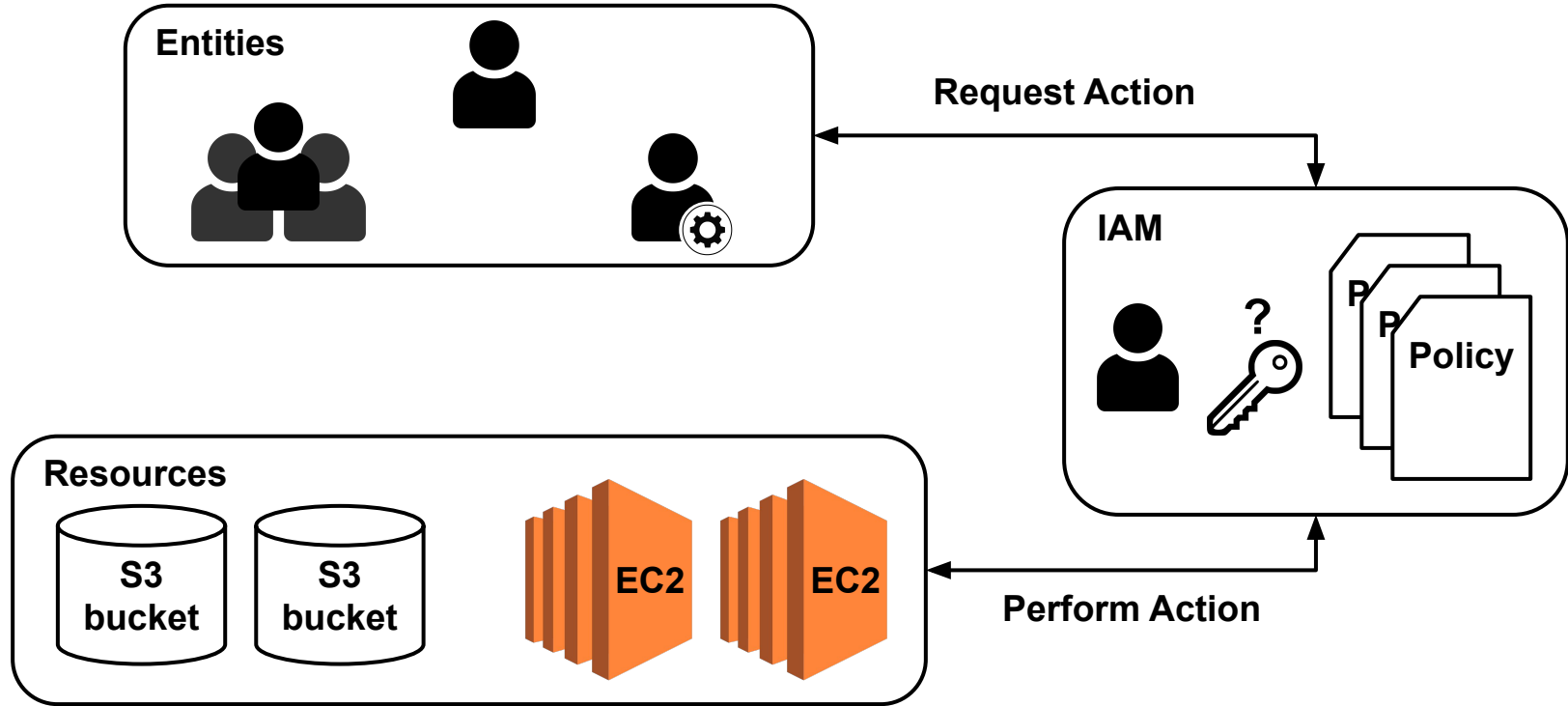


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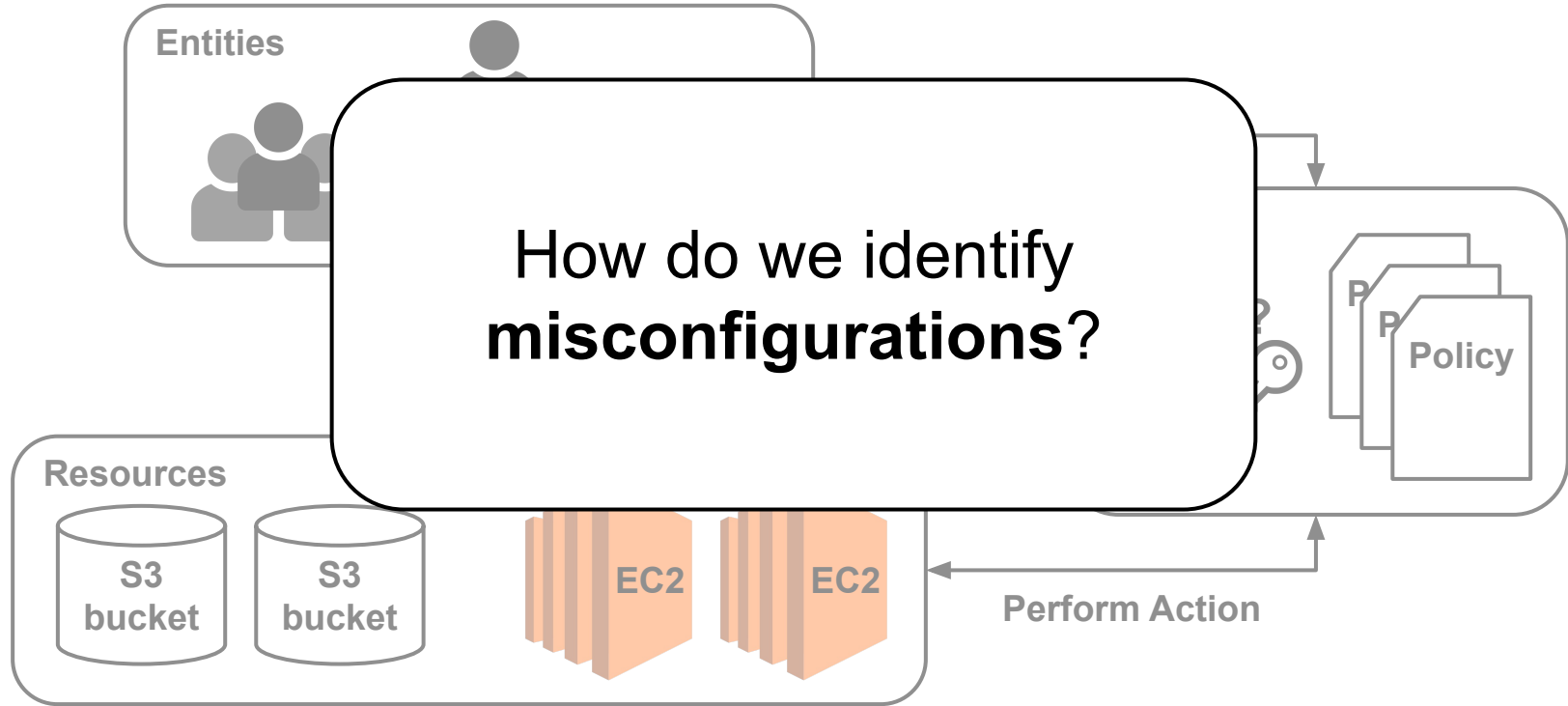




# Identity and Access Management



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# Existing solutions

- Cloud Custodian

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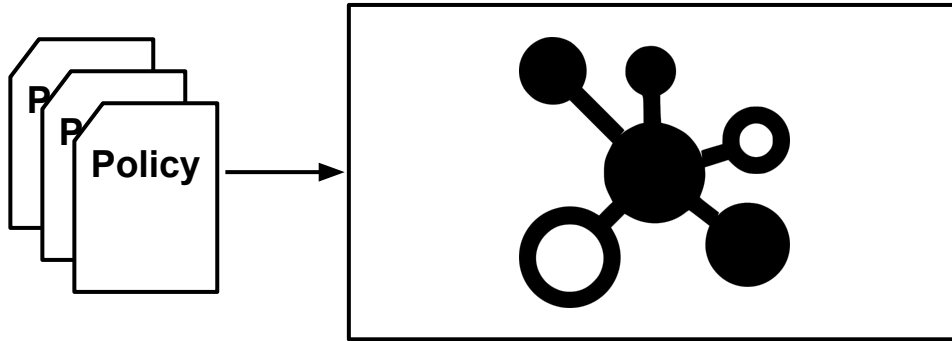
- Cloud Custodian
  - Rule-based
  - Requires manual tweaking of rules
- P-Diff
  - Learns control policies from access logs
  - Reactive approach

# Idea

- Most policies are properly configured

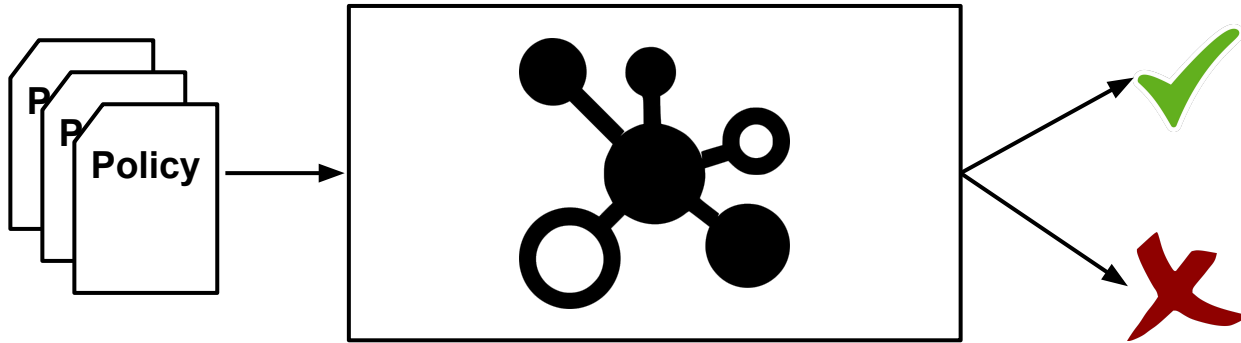
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- Most policies are properly configured
- Use **anomaly detection** to learn properly configured policies



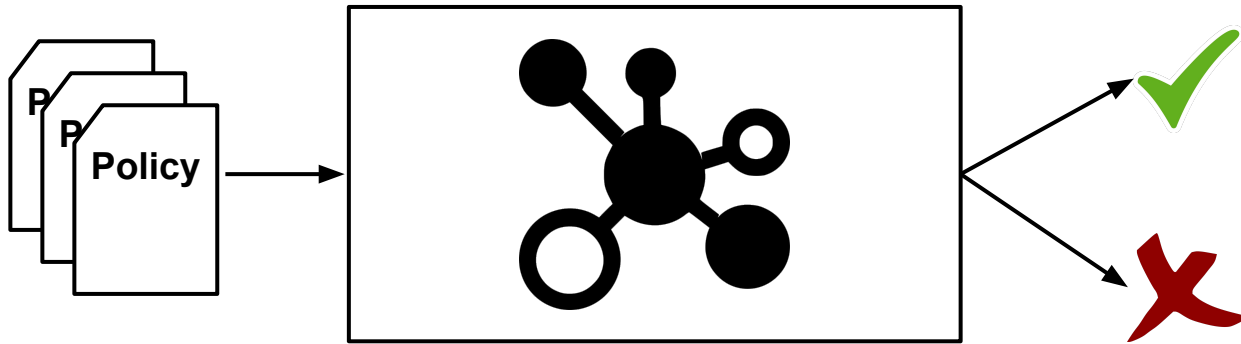
# Idea

- Most policies are properly configured
- Use **anomaly detection** to learn properly configured policies
- Any found **anomalies** will likely be **misconfigurations**



# Challenges

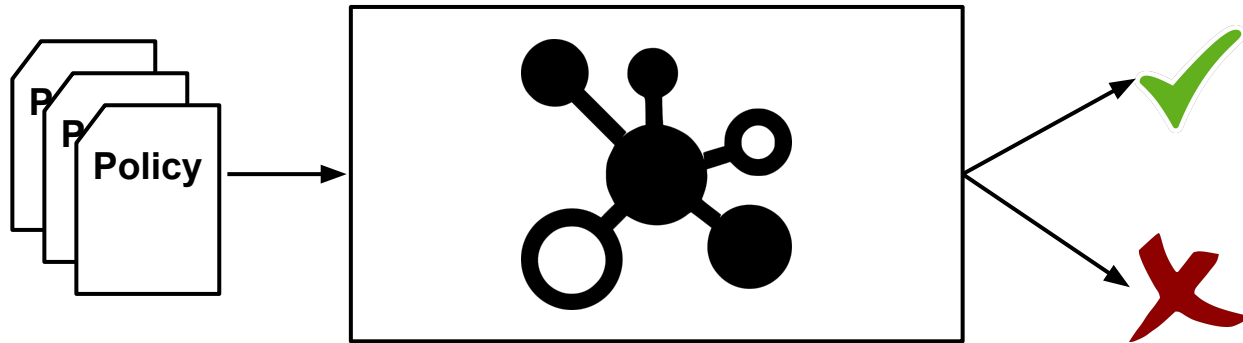
- Policies are **specific** to the **context** of the organization





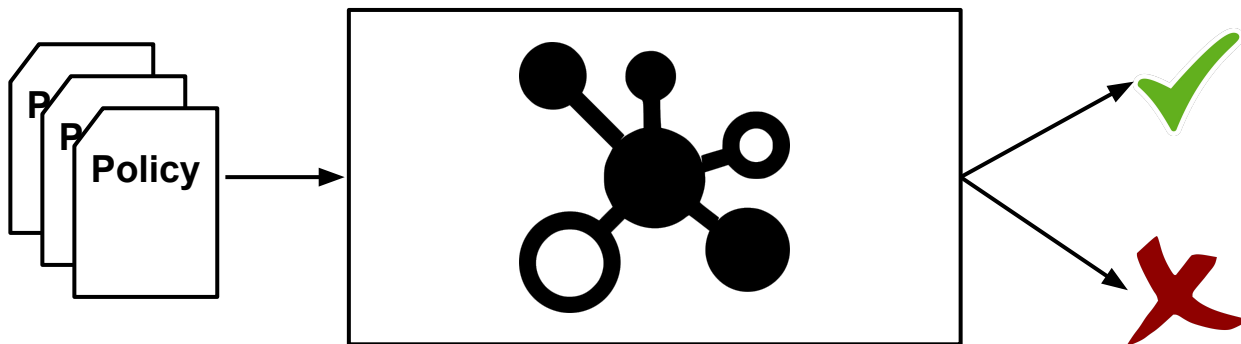
# Challenges

- Policies are **specific** to the **context** of the organization
- Checks must be **proactive** to ensure policies are not abused



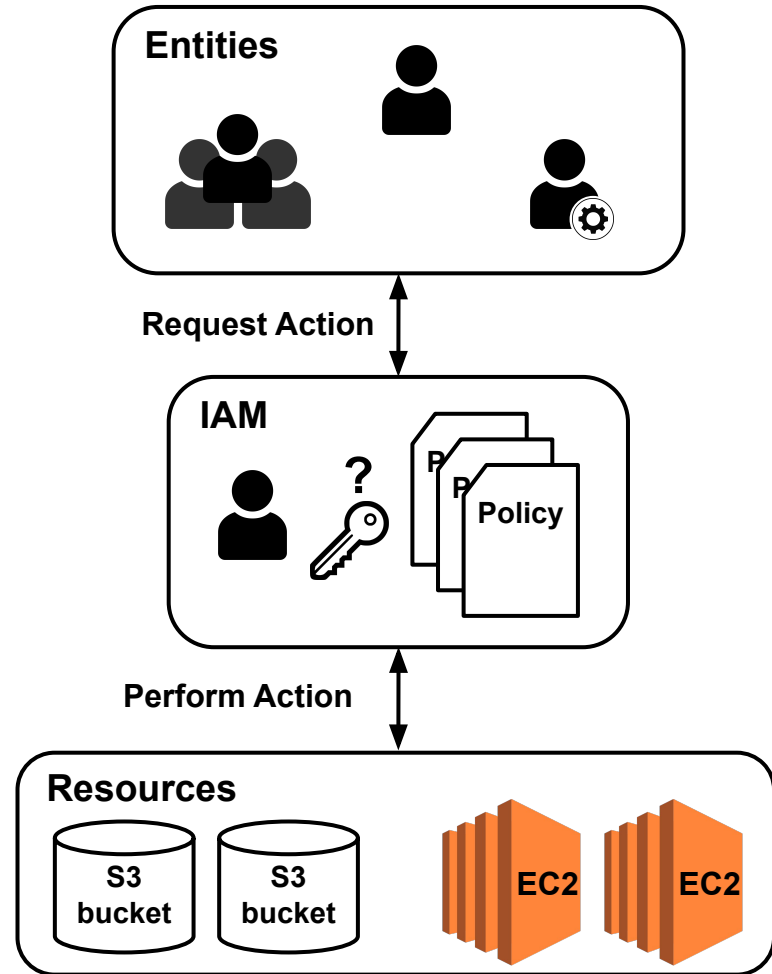
# Challenges

- Policies are **specific** to the **context** of the organization
- Checks must be **proactive** to ensure policies are not abused
- Checks must be **low maintenance** to ensure adoption



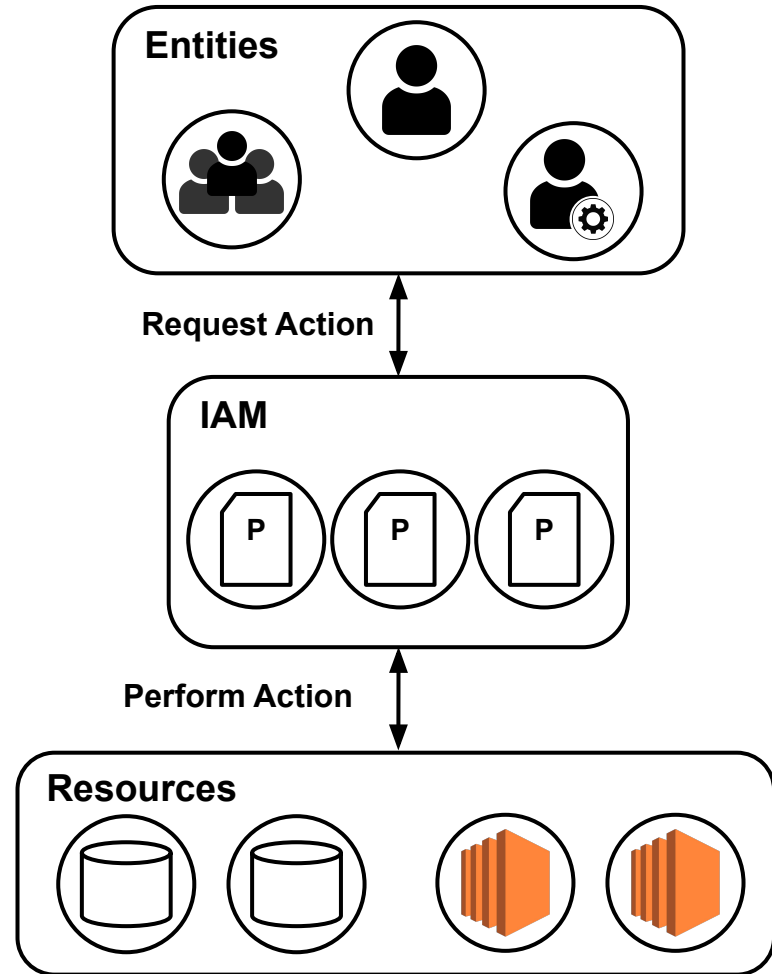
# Approach

- Model policies as a graph



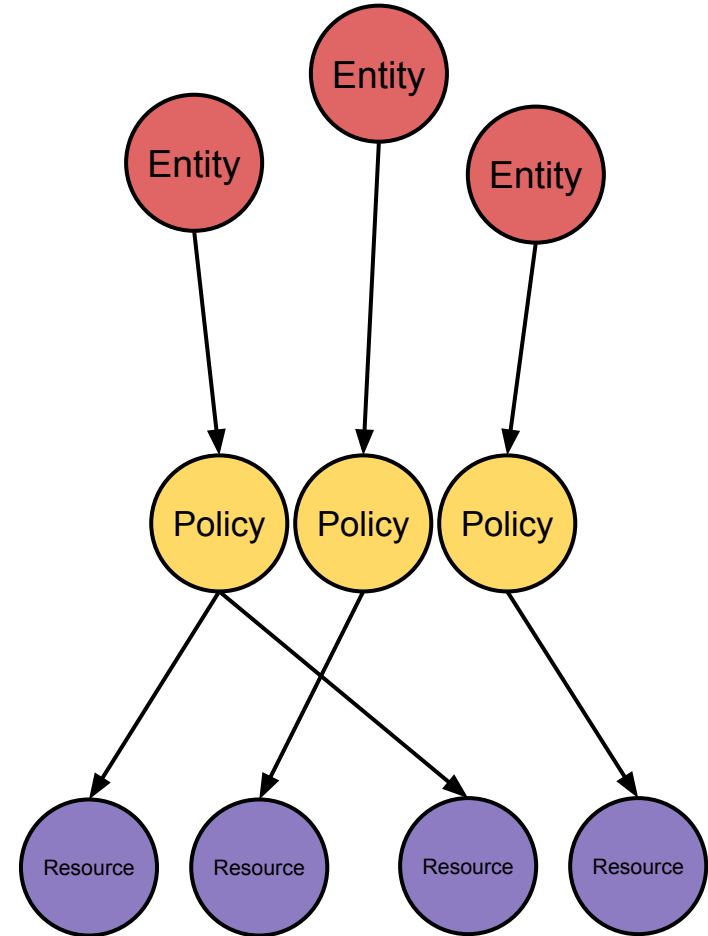
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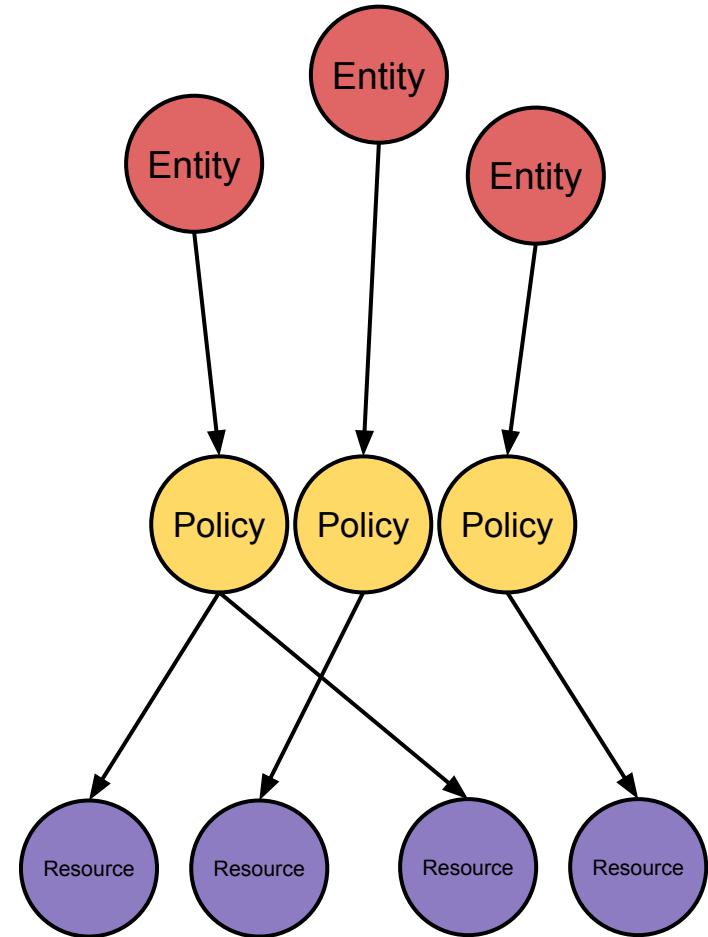
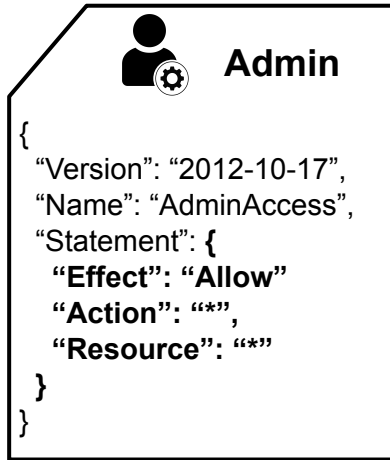
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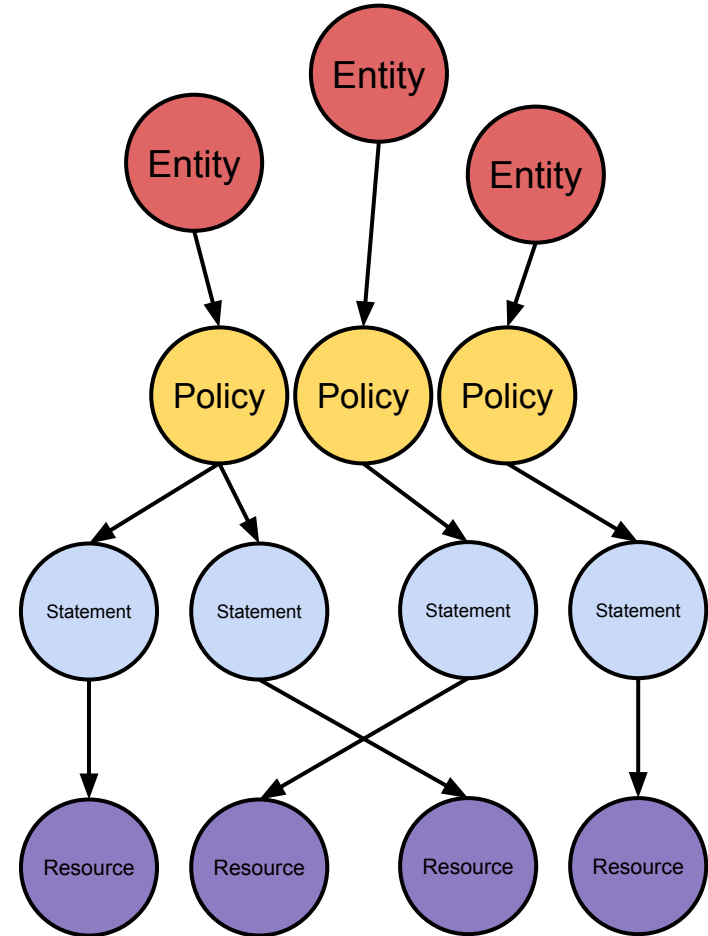
# Approach

- Model policies as a graph
  - A policy can have multiple statements



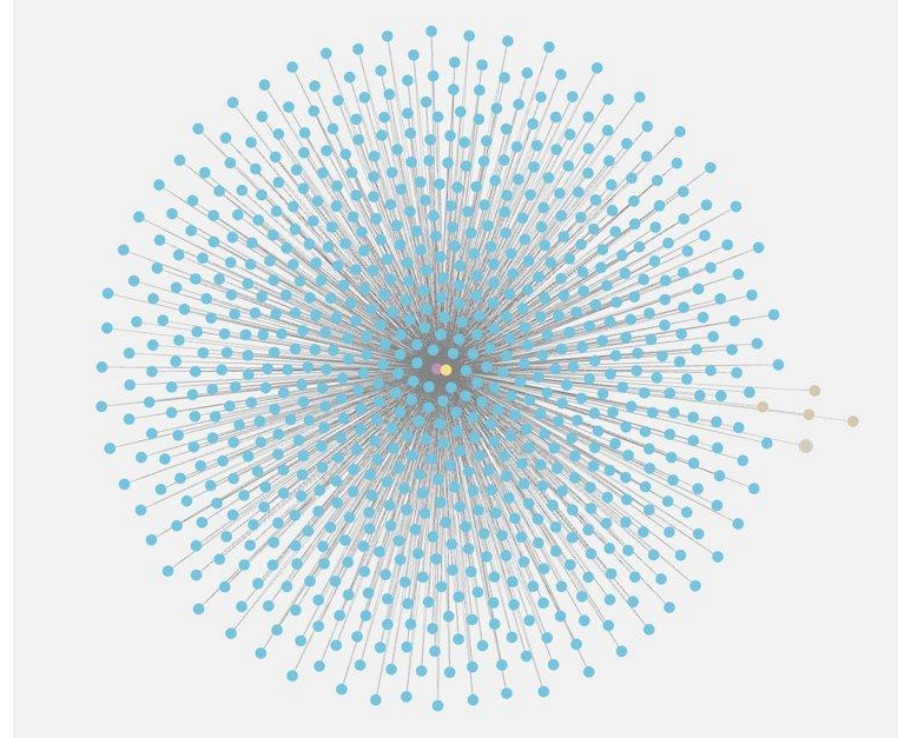
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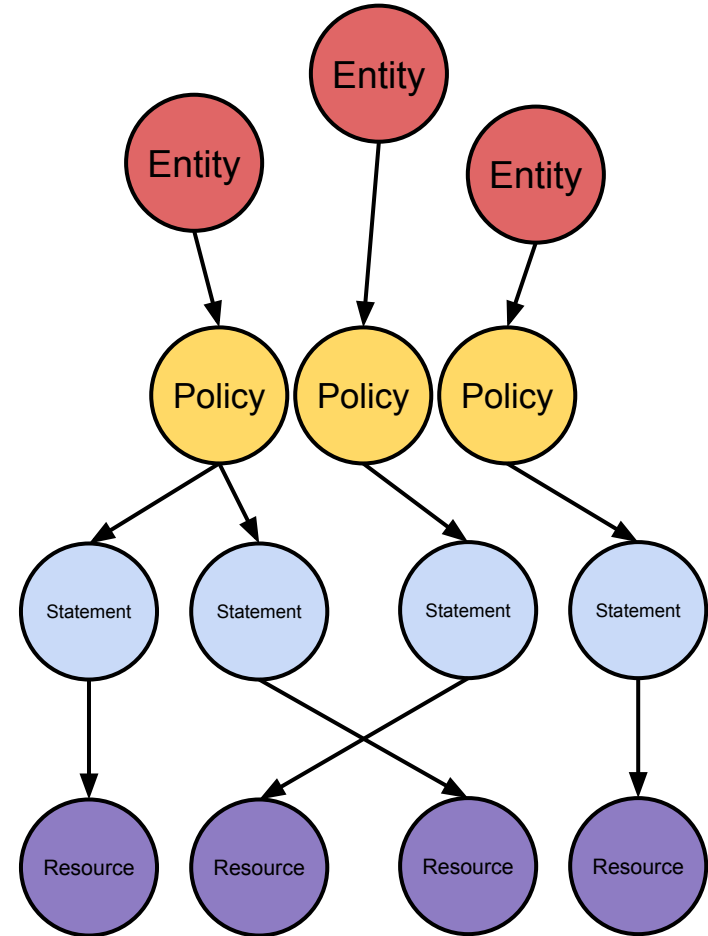
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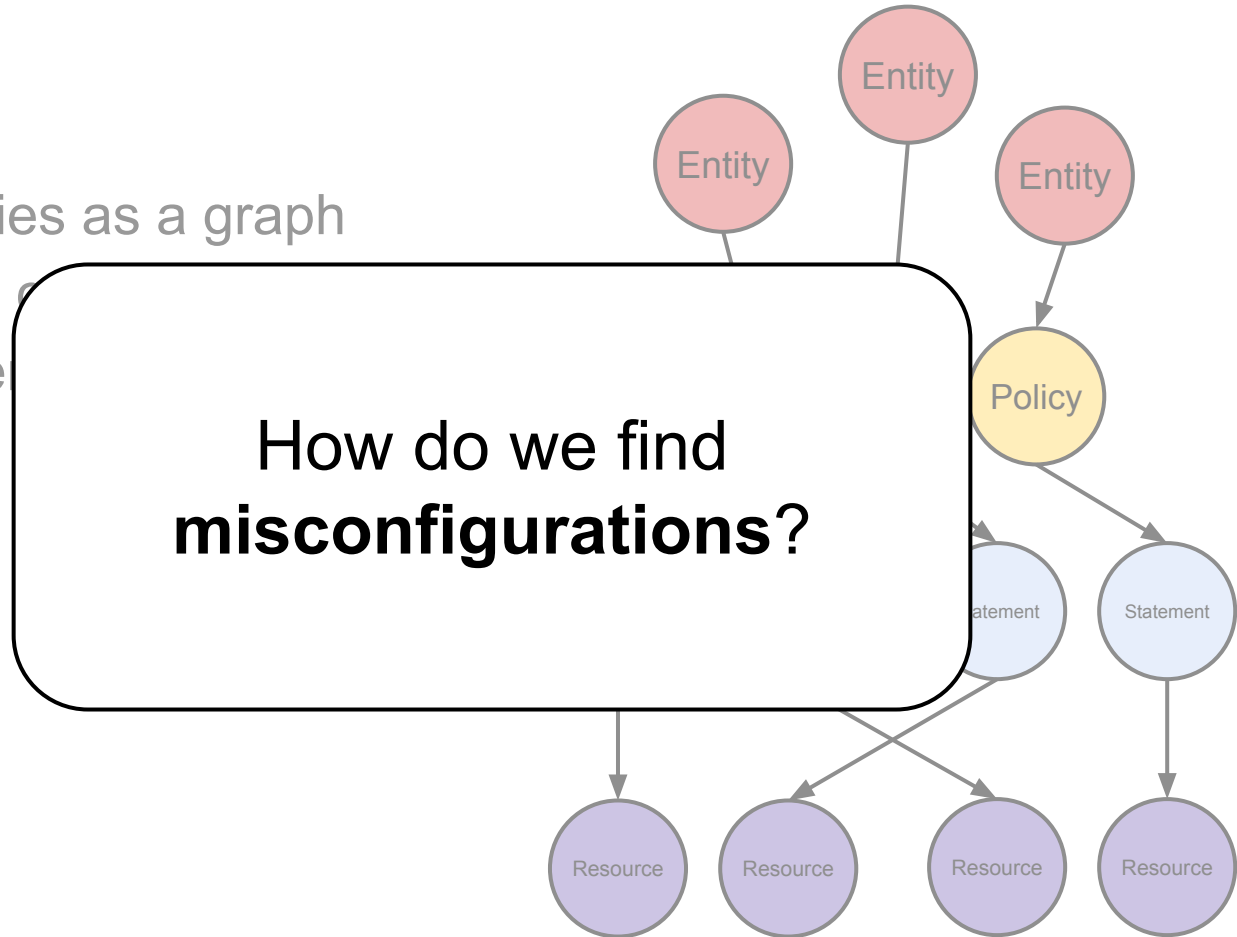
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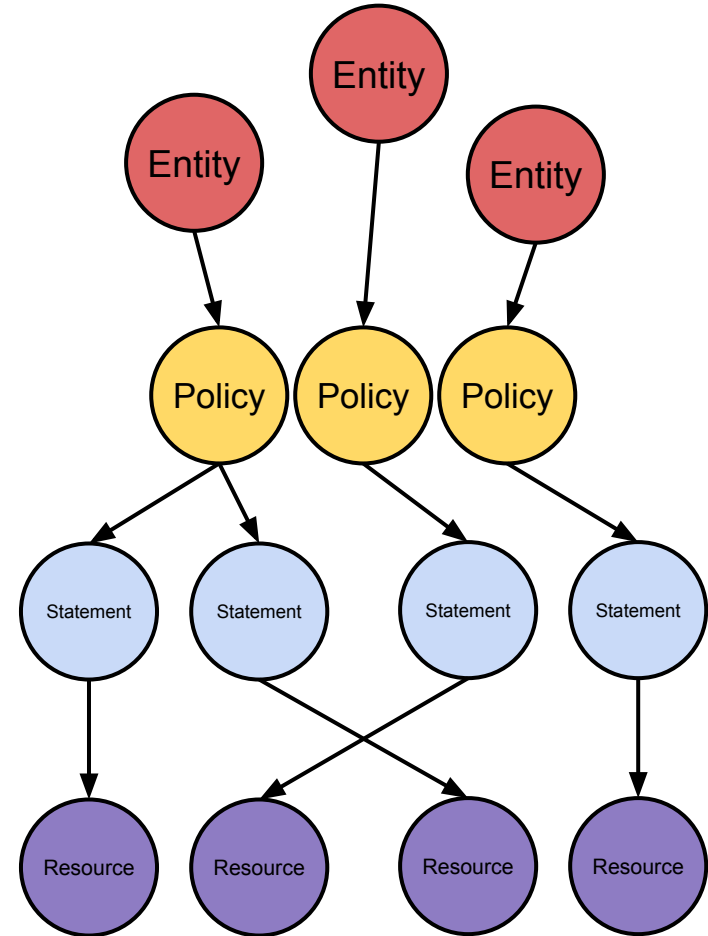
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- Model policies as a graph
  - A policy consists of a set of statements



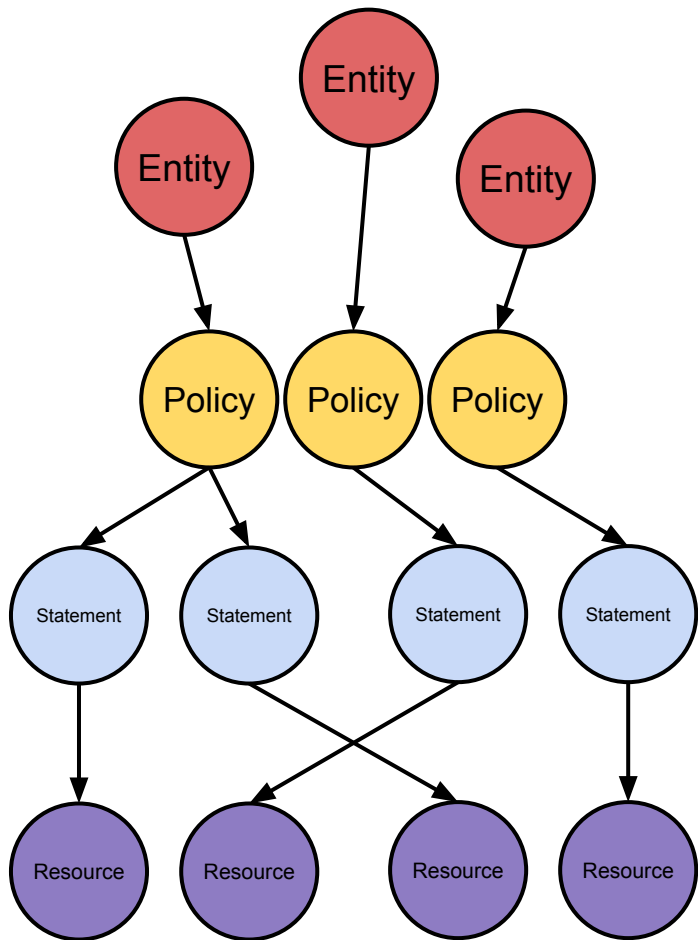
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- Model policies as a graph
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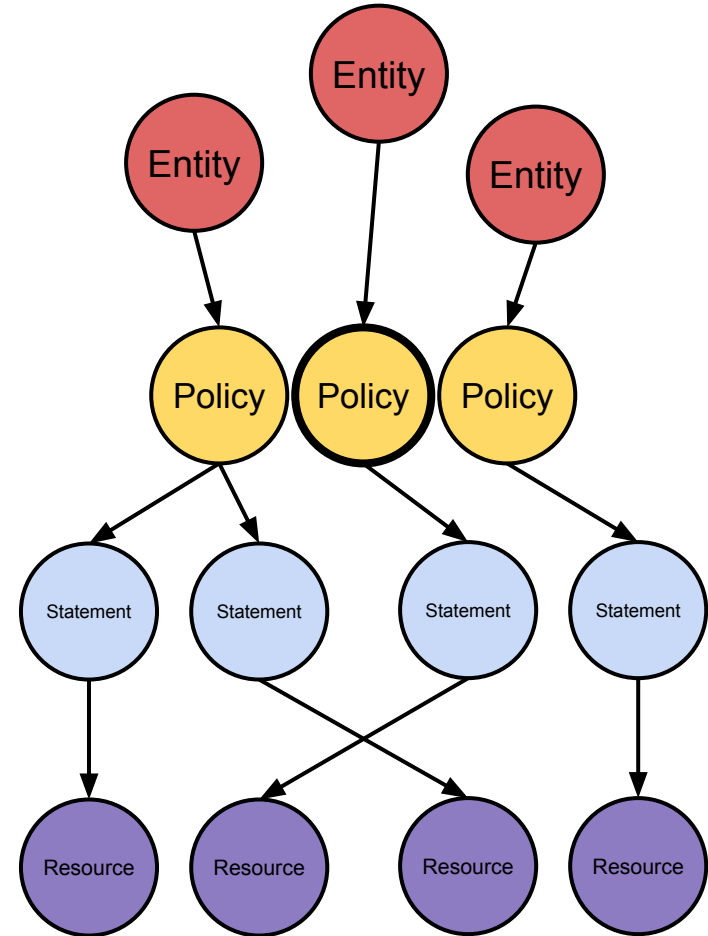
# Approach

- Model policies as a graph
  - A policy can have multiple statements
- Policies are **specific** to the **context** of the organization
- Model the context of policies using **Node2vec**



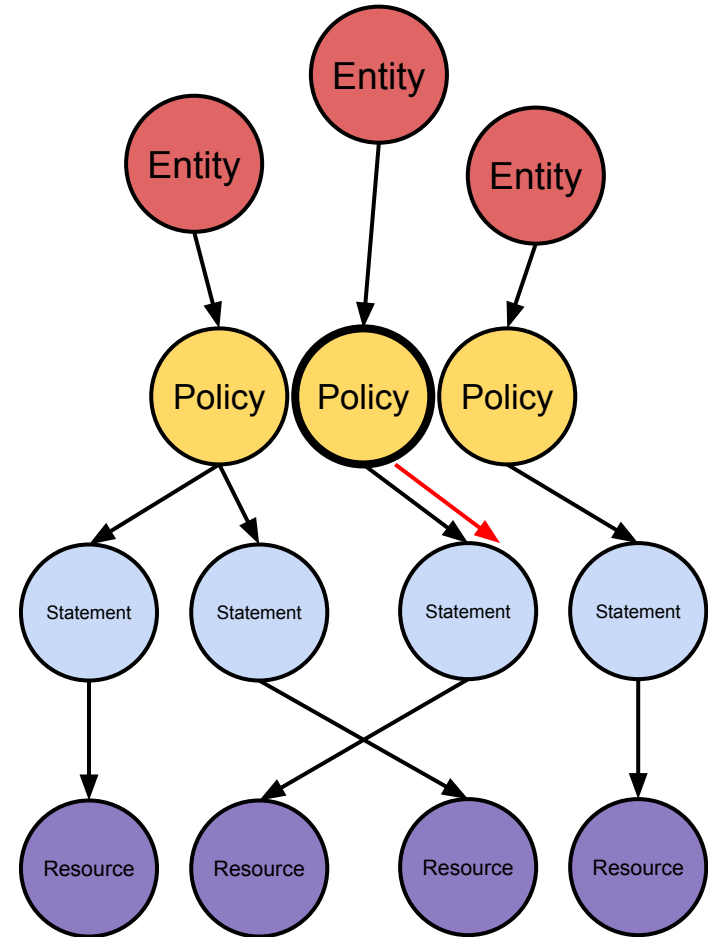
# Approach - Node2vec

- Select a starting **policy node**



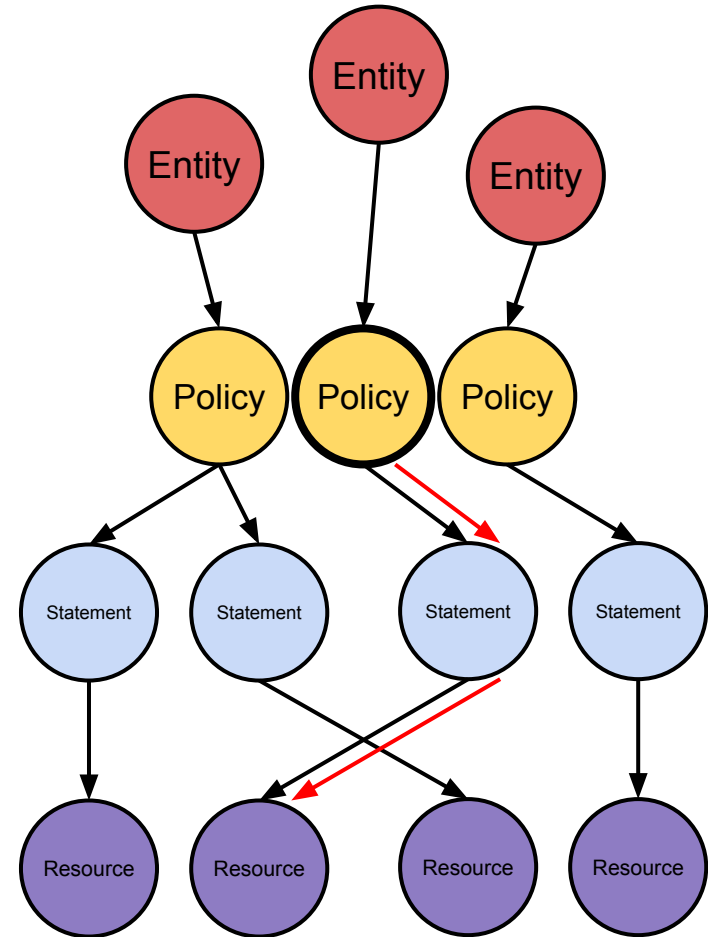
# Approach - Node2vec

- Select a starting **policy node**
- Perform random walks



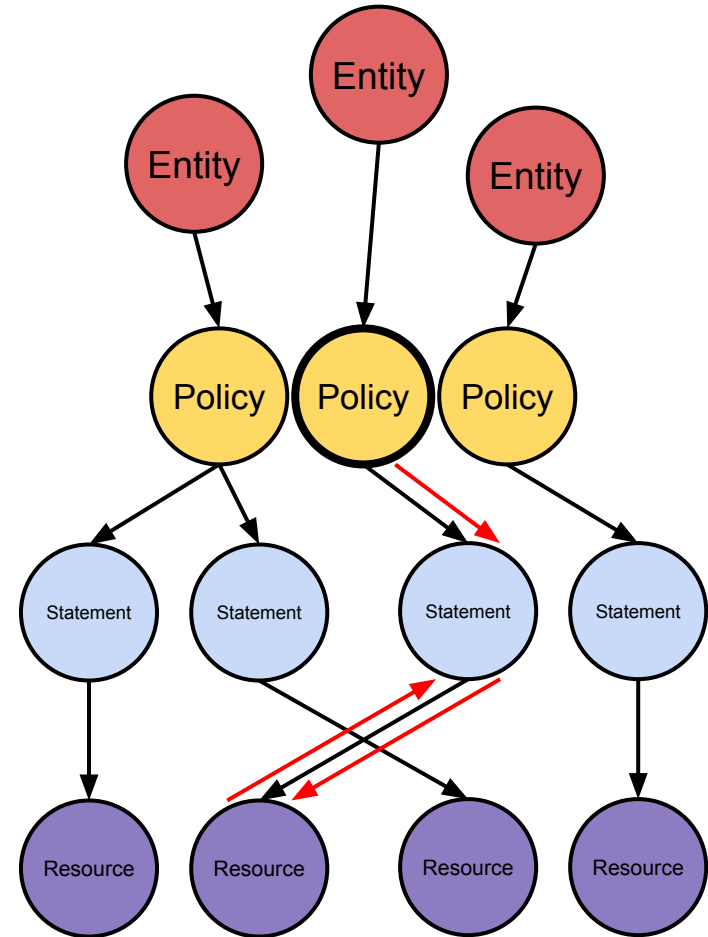
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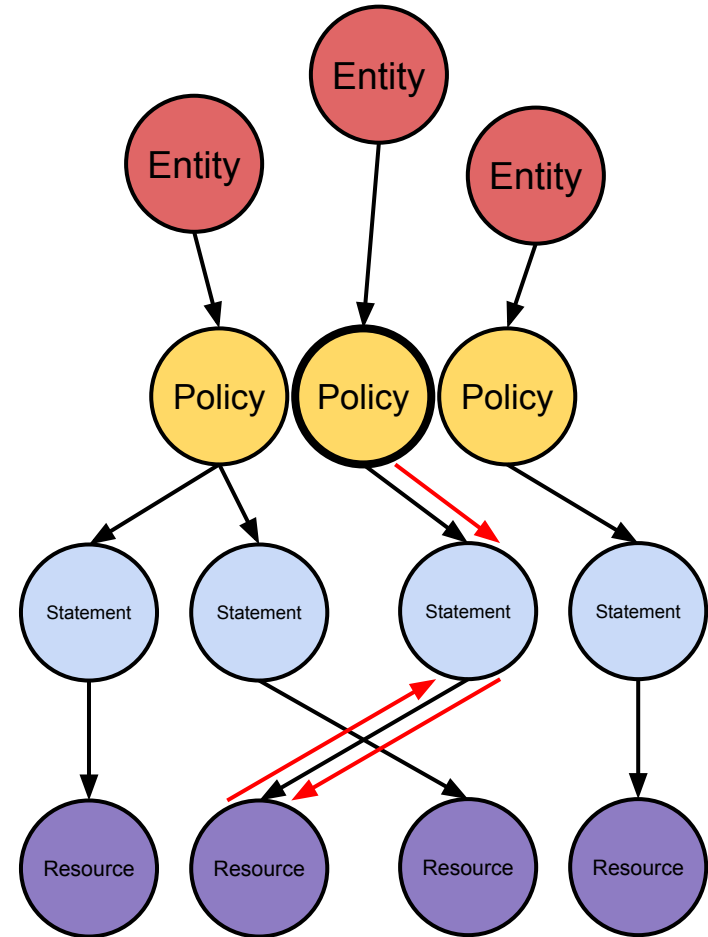
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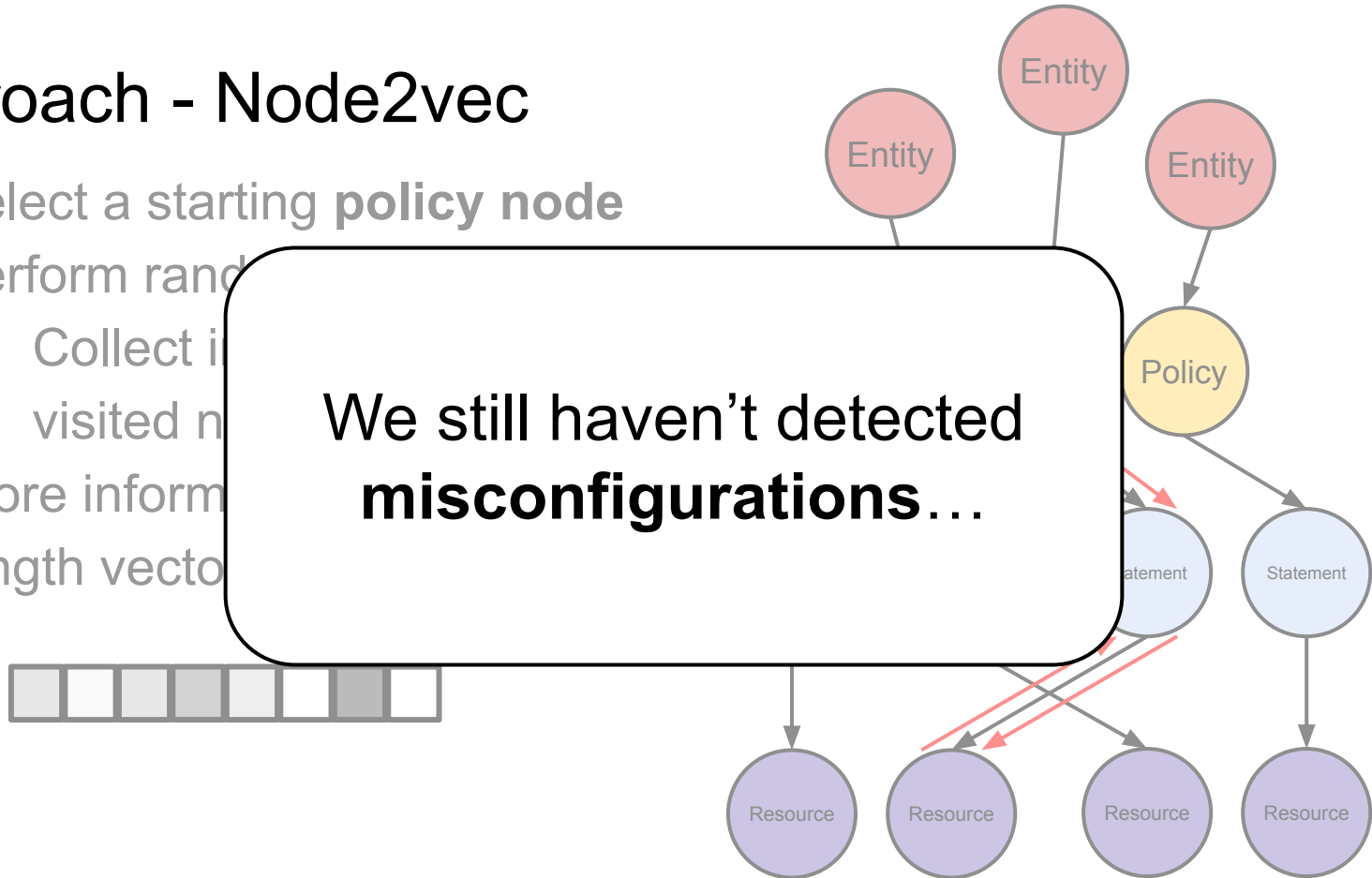
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- Select a starting **policy node**
- Perform random walks
  - Collect information about visited nodes and edges
- Store information in a fixed length vector



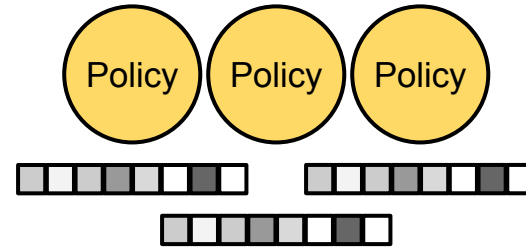
# Approach - Node2vec

- Select a starting **policy node**
- Perform random walk
  - Collect information from visited nodes
- Store information as length vector



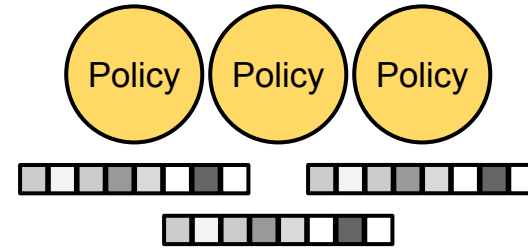
# Approach - Anomaly detection

- Each policy node is represented by a vector



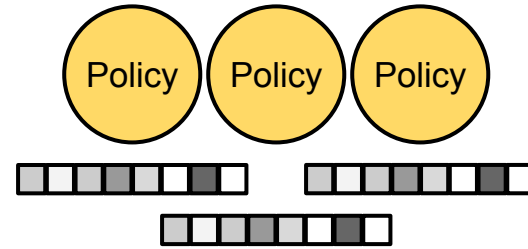
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- Each policy node is represented by a vector
- We can train an anomaly detection model to find anomalous policies



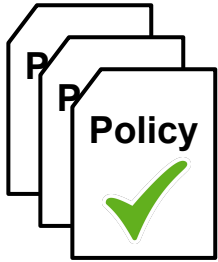
# Approach - Anomaly detection

- Each policy node is represented by a vector
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  - One-Class SVM
  - Local Outlier Factor
  - Isolation Forest
  - Robust Covariance



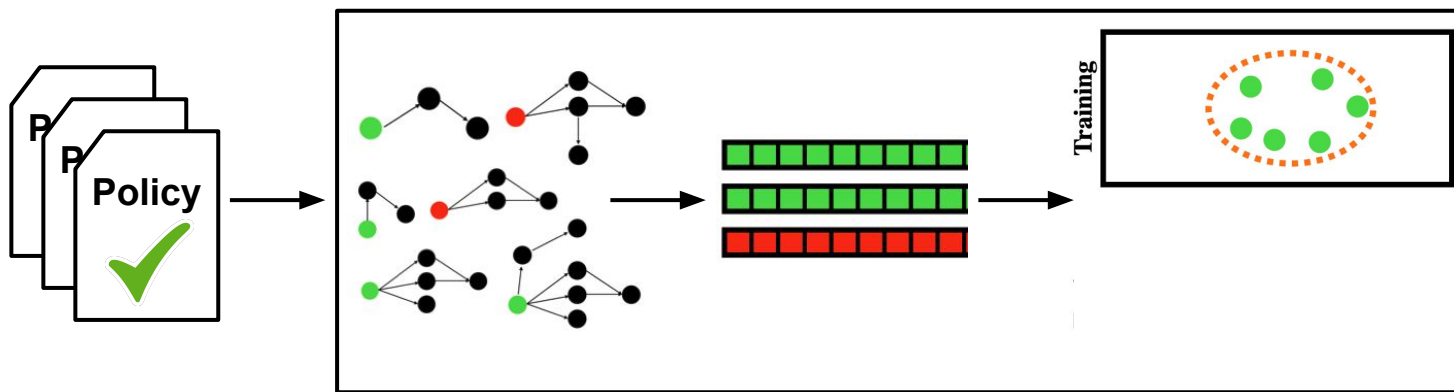
# How does this work in practice?

- Security operators manually verify a set of policies



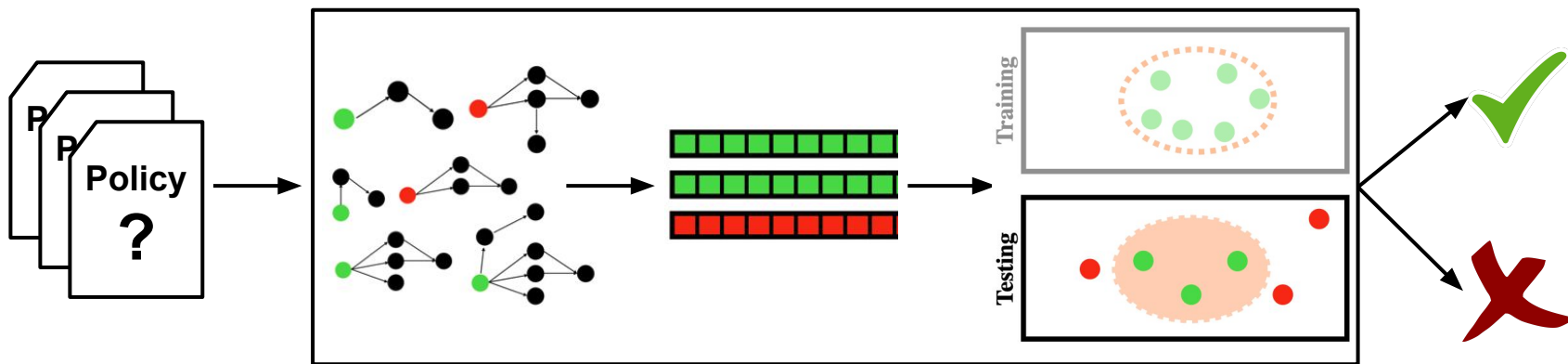
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# How does this work in practice?

- Security operators manually verify a set of policies
- We run our approach and train the anomaly detector
- When new policies are added, we run our pipeline to check if we find an anomaly





# Evaluation - Are anomalies misconfigurations?

- Evaluated on 3 real-world datasets

| Dataset | Total number of |          |       |        |       | Number of collections |
|---------|-----------------|----------|-------|--------|-------|-----------------------|
|         | employees       | policies | users | groups | roles |                       |
| 1       | 12,000          | 842      | 0     | 0      | 55    | 8                     |
| 2       | 130             | 812      | 0     | 0      | 34    | 2                     |
| 3       | 4               | 826      | 2     | 1      | 10    | 12                    |

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  - Dataset 1 & 2 are SSO users

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# Evaluation - Are anomalies misconfigurations?

- Evaluated on 3 real-world datasets
  - Dataset 1 & 2 are SSO users
  - Data was periodically collected using our tool

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- Increased detection of **misconfigurations**

|          |    | Our approach |        |          | Cloud Custodian<br>All rules |        |          | Cloud Custodian<br>Selected rules |        |          |
|----------|----|--------------|--------|----------|------------------------------|--------|----------|-----------------------------------|--------|----------|
|          | DS | Prec.        | Recall | F1-score | Prec.                        | Recall | F1-score | Prec.                             | Recall | F1-score |
| Misconf. | 1  | 66.67%       | 66.67% | 66.67%   | 7.89%                        | 10.34% | 4.48%    | 100.00%                           | 10.34% | 9.37%    |
|          | 2  | 70.00%       | 63.34% | 66.67%   | 13.73%                       | 17.07% | 7.61%    | 100.00%                           | 17.07% | 14.58%   |
|          | 3  | 75.00%       | 50.00% | 60.00%   | 15.38%                       | 11.32% | 6.52%    | 100.00%                           | 11.32% | 10.17%   |
| Overall  | 1  | 91.58%       | 91.58% | 91.58%   | 97.93%                       | 97.60% | 97.76%   | 98.99%                            | 98.98% | 98.57%   |
|          | 2  | 92.03%       | 92.31% | 92.15%   | 97.40%                       | 97.09% | 97.24%   | 98.75%                            | 98.73% | 98.28%   |
|          | 3  | 94.97%       | 95.45% | 95.03%   | 98.93%                       | 97.88% | 96.87%   | 98.12%                            | 98.08% | 97.33%   |

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- Increased detection of **misconfigurations** but more **FPs**

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Precision and recall can be **tuned** in anomaly detector

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# Conclusion

Using **anomaly detection** in IAM policies:

- **Increases** the number of detected **misconfigurations**
- **Incorrectly** flags **slightly more** policies than rule-based solutions
- Requires **fewer** manual steps than rule-based solutions

`https://github.com/utwente-scs/misdet-code`



# Questions?

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Thijs van Ede

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🐦 @EdeThijs



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