

### **Validating Damage Assessment: A Simulation-Based Analysis of Blind Write Lineage in Fog Computing**

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Presented by

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*Ph.D. Candidate in Computer Science, University of Arkansas* •**Focus**:

Database security with expertise in damage assessment, recovery algorithms •**Experience**:

Research Assistant, Database Security, University of Arkansas

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### •**Publications**:

Damage Assessment in Fog Computing Systems: Developed a novel blind write lineage approach for secure IoT, presented at the SIoTEC Workshop 2024.

•**Projects**: Developed a malware classification tool using Pyramid Vision Transformer achieving 94.8% accuracy.



### **Contents**

### Introduction:

- Fog computing Overview
- Problem Statement

### Motivation

• Why Fog Systems Need Faster Recovery?

Key Concepts Blind Write Lineage Model Key Components of the Model Cases of Blind Write Lineage Model Damage Assessment Approach Simulation Setup Simulation Results Conclusion



# Fog Computing Overview

- Extension of cloud computing
- Brings computing resources closer to end users
	- Key characteristics:
		- Low latency
			- ➢ Real-time interaction
			- ➢ Heterogeneity

### • Benefits:

➢ Reduced network congestion

➢ Improved response times

➢ Enhanced data security and privacy





### Problem Statement





# Motivation





# Key Concepts

### **Blind Writes** • Write operations that update data without reading existing values • Characteristics: ➢No prior read request ➢Modification occurs regardless of original value ➢Absence of pre-write read operation

**Importance**

#### **Benefits**

- Minimizes damage assessment time
- Accelerates damage recovery process
- Reduces system downtime during attacks

#### **Data Dependencies**

- Relationships between data items tracked for damage assessment
- Types:
	- Direct dependencies (parent-child)
	- Indirect dependencies (ancestor-descendant)

•Enables tracing of damage propagation •Facilitates efficient isolation of compromised data •Crucial for targeted recovery efforts



# Blind Write Lineage Model





# Blind Write Lineage Model





# Key components of the model





# Key components of the model





# Key components of the model(Example)







Figure 2: Multiple subgraphs in the data dependency (G)



# Cases of Blind Write Lineage Model

Case 1: Single-Parent/Single-Child Lineage

- Data items are updated sequentially, each relying on a single predecessor.
- The lineage traces back to the original blindly written item.

### **Key Points**

Simple and direct lineage.

Easy to trace damage

propagation.



Figure 3: Single-Parent/Single-Child Lineage





# Cases of Blind Write Lineage Model

Case 2: Multipath Lineage

- More complex scenario where a child node might have multiple parent nodes.
- Data items may be updated using multiple arguments.



Figure 4: Complex Blind write Lineage.





# Damage Assessment

### **Objective:**

•Quickly identify and isolate compromised data in fog computing systems

### **Challenges:**

- Rapid propagation of damage
- Complex data dependencies
- Need for real-time recovery

**Key Concepts in Damage Assessment:**

### •**Attack Time**  $(t_{q})$ :

- $\triangleright$  Time when the malicious transaction occurred
- $\triangleright$  Crucial for determining the timeline of damage.

### •Last Updated Time  $(t_{last\ updated\ time})$ :

- $\triangleright$  Last time each data item was updated
- Helps in assessing whether an item was affected post-attack.

### **•Affected Time**  $(t_{aff})$ :

- $\triangleright$  Time when a data item was affected by the attack
- $\triangleright$  Helps in assessing whether an item was affected post-attack.



# Damage Assessment





# Damage Assessment(Example)



Figure 5: Multiple subgraphs in the data dependency (G).

### **Scenario (a):**

•Table 1 shows that data item *C* was last updated at  $t_{19}$ .

•This update occurred in the damaged graph  $G<sub>2</sub>$ (shaded part).

•Since *C* is updated within the same damaged graph, it remains compromised.

### TABLE 1: FINAL UPDATED TIMETABLE (FOR SCENARIO (A))



#### TABLE 2: FINAL UPDATED TIMETABLE (FOR SCENARIO (B))



### **Scenario (b):**

- •Table 2 shows that data item  $C$  was last updated at  $t_{16}$ .
- •This update occurred in a separate graph  ${\sf G}_{3}$ .

•Although *C* is a child of the initially damaged data item *S*, its update in a different graph signifies it is safe for release.



# Simulation Setup

### **Objectives:**

Evaluate the efficiency and effectiveness of the Blind Write Lineage model in damage assessment.

### **Variables Considered:**

1.Number of Transactions: 200 to 900 2.Number of Data Items: 500 to 3000 3.Max Operations per Transaction: 3 to 12 4.Max Write Operations: 1 to 5 5.Number of Blind Writes: 1% to 10% of transactions



### *Varying the number of transactions*

- As the number of transactions increases, the average data item reads in traditional logs rise gradually.
- This increase is due to more transactions leading to a higher number of blind writes and more subgraphs.
- The average data item reads remain relatively constant and significantly lower compared to traditional methods.
- This stability is attributed to consistent average dependency per graph, even with more transactions.



Figure 6: Varying the number of transactions.



### *Varying the number of data items.*

- Significant decrease in average data reads after identifying damaged data using our method compared to traditional methods.
- The graph remains relatively consistent despite variations in the number of data items.
- This consistency is due to the fixed number of blindwritten data items and written data items per transaction. Previously written items are often read later to write new items, leading to consistent behavior.



Figure 7: Varying the number of data items.



### *Varying the Max number of operations per transaction.*

- Both methods show an increase, but our method maintains significantly lower average reads compared to traditional transactions.
- More operations per transaction lead to more read items. Increased dependency results in more data to read.
- Despite the gradual increase in reads, our method remains efficient, highlighting its effectiveness in managing dependencies even with higher operation counts. This explains the gradual increase observed in the graph.



Figure 8: Varying the Max number of operations per transaction.



#### *Varying the Number of blind write per transaction*

- Our method shows a gradual decrease in average data reads. In contrast, normal transactions maintain relatively constant reads.
- In our method, as the number of blind writes increases, the number of subgraphs also increases. Consequently, the number of data items depending on each subgraph decreases, leading to a decrease in the average reading. The average reading.





### *Varying the Max write operations.*

- In traditional method, average data reads remain relatively constant.
- In our method, gradual increase in average data reads can be seen because more write operations lead to increased dependency.
- Fixed blind writes mean more data items are written after being read, increasing dependencies. Figure 10: Varying the Max write operations.





# Conclusion

•Introduces an efficient technique for rapid damage assessment in fog computing systems •Addresses limitations of traditional log analysis methods •Leverages blind write lineage for efficient damage tracing •Performance Advantages:

•Superior speed in damage assessment •Enhanced efficiency in data recovery •Improved accuracy compared to traditional methods

•Future Work:

•Refine model for specific time-range attacks. •Optimize memory usage with efficient data structures. •Ensure scalability across diverse architectures. •Explore blockchain for secure transaction logging.



# Thank You