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Runtime Prevention of Deserialization Attacks

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Problem and Proposed Solution

- Untrusted deserialization exploits, where a serialised object graph (i.e. gadget chain) is used to achieve denial-of-service or arbitrary code execution were introduced in the 2017 OWASP Top 10 and merged in the broader "injection" category in the 2021 version.
- State-of-the-art approaches (e.g. JDK¹ deserialization filters), ask developers to block or allow classes individually, without any context, despite the sequential nature of gadget chains.
- We show how Markov chains can help detect sequences of features that are typical of gadget chains to detect and prevent deserialization attacks.

[1]: JDK is a registered trademark of Oracle and/or its affiliates. Other names may be trademarks of their respective owners.





[1]: Java is a registered trademark of Oracle and/or its affiliates. Other names may be trademarks of their respective owners.



What Makes A Good Gadget Chain?

"A whole is what has a beginning and middle and end"

Aristotle, Poetics (335 BCE)



What Makes A Good Gadget Chain?

Aristotle got it right. A good gadget chain needs:

- A method that will be called at the *beginning* of deserialisation to hand control to...
- Linker classes in the *middle* that will set the scene for...
- The target method that will be invoked at the *end* of deserialisation.

Aristotle, Poetics (335 BCE)

Hypothesis



The sequence of classes and their features differ significantly between benign and malicious deserialization chains.

Modelling Java Deserialisation as Markov Chains (1)

Given a class C and a set of Boolean class features F, we can abstract C to a set of Boolean features f:

$$C \to f, f \in P(F)$$

Similarly, we can abstract any gadget chain G as a sequence of feature sets:

$$G \to (f_1, f_2, \cdots, f_{n-1}, f_n), f_i \in P(F)$$



Graphically:

Features - From Manual Review of ysoserial Gadget Chains

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ld	Feature	Description True if the class calls any of the following from java.lang.reflect: - Constructor.newInstance() - Field.set() - Method.invoke()			
1	Uses reflection				
2	Overrides readObject	True if the class overrides the method Object <pre>readObject(ObjectInputStream</pre>			
3	Overrides hashCode	True if the class overrides the int hashCode() method.			
4	Has generic field	<pre>True if the class has a field of any of the following type: - java.lang.Object - java.lang.Comparable - java.util.Comparator</pre>			
5	Implements Map	True if the class implements the java.util.Map interface.			
6	Implements Comparator	True if the class implements the java.util.Comparator interface.			
7 Calls hashCode - int java.util.Objects.hash(Object		<pre>True if the class calls any of the following methods: - int java.util.Objects.hash(Object values) - int java.util.Objects.hashCode(Object o) - *.hashCode()</pre>			
8 nt © 202	Calls compare 22, Oracle and/or its affiliates	<pre>True if the class calls any of the following methods: - *.compare() - *.compareTo()</pre>			

Modelling Java Deserialisation as Markov Chains (2)

A Markov chain represents a system that:

• Has a finite number of states:

$$S = \{s_1, s_2, \cdots, s_n\}$$

• Starts in any given state $s \in S$ with probability $p_i \in p_{init}$, its initial state probability vector:

$$p_{init} = (p_1, p_2, \cdots, p_n)$$

• Transitions between states with some probability *p* at each step *t*:

$$p_{tr} = \begin{pmatrix} p_{11} & \cdots & p_{1n} \\ \vdots & \ddots & \vdots \\ p_{n1} & \cdots & p_{nn} \end{pmatrix}$$

Modelling Java Deserialisation as Markov Chains (3)

Given a Markov chain and an observed sequence of states, one can estimate the probability that the chain generated the sequence with a simple product of probabilities:

$$p(f_1, f_2, \cdots, f_n) = p_{init}(f_1) \cdot \prod_{i=2}^n p_{tr}(f_{i-1}, f_i)$$



Estimating Transition Probabilities From Data

Our goal is to build two Markov chains *B* and *M* from benign and malicious datasets respectively.

Empirical approach:

Use the observed transition probabilities directly. Works well with large dataset.

Bayesian approach:

Model each row of p_{tr} as the output of a known probability distribution (i.e. Dirichlet) and explore the space of Dirichlet parameters $\alpha = (\alpha_1, \alpha_2, \dots, \alpha_K)$ to find the distribution **s** $Dir(\alpha_i)$ that best characterize the data.

Black magic involving probabilistic programming (Bayesian inference), Dirichlet distributions, and Markov Chain Monte Carlo sampling...

Output: Two sets of benign (*B*) and malicious (*M*) Markov chains

Creating A Deserialization Dataset (1)

Ysoserial is a public repository of deserialization gadget chains.

- 1. Create an ASM agent to dynamically extract features from loaded classes.
- 2. Build a harness to (de)serialise ysoserial payloads, and extract features.



Creating A Deserialization Dataset (2)



ORACLE WebLogic Server

WebLogic Server (WLS)¹ heavily relies on deserialisation for common operations.

- 1. Instrument WebLogic Server with the ASM agent mentioned above.
- 2. Load WLS and exercise its console to extract features from "benign" deserialization chains .

[1]: Oracle®WebLogic Server is a registered trademark of Oracle and/or its affiliates. Other names may be trademarks of their respective owners.

Dataset Description



	Unique chains	Average length	Median length
Benign (WLS)	227	38.96	13
Malicious (ysoserial)	37	16.68	6

Detecting Deserialization Attacks

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Input: \mathcal{B} , \mathcal{M} , t, I **Output:** status \in {accepted, rejected, undecided} 1 $seq \leftarrow \text{new List}()$ **2 Function** *MarkovFilter(class, end)*: $features \leftarrow \text{EXTRACTFEATURES}(class)$ 3 seq.append(features) 4 $\overline{P_{\mathcal{B}}} \leftarrow mean(P(seq \mid \mathcal{B})))$ 5 $\overline{P_{\mathcal{M}}} \leftarrow mean(P(seq \mid \mathcal{M}))$ 6 $disjoint \leftarrow ((\overline{P_{\mathcal{B}}} \pm \mathbf{t}\sigma) \cap (\overline{P_{\mathcal{M}}} \pm \mathbf{t}\sigma) = \emptyset)$ 7 if end and disjoint then 8 return $\overline{P_{\mathcal{M}}} > \overline{P_{\mathcal{B}}}$? rejected : accepted 9 else if end and $\neg disjoint$ then 10 return rejected 11 else if disjoint and $|seq| \ge I$ and $\overline{P_M} > \overline{P_B}$ then 12 return rejected 13 else 14 return undecided 15 end 16 Copyright @12022, Oracle and/or its affiliates

Bayesian vs. Empirical, 5-Fold Cross-Validation

	t	Precision	Recall	F1-score	Time (sec)
	0	91.67±6.97	96.67±6.67	0.94±0.03	7163
Payasian	1	91.67±6.97	96.67±6.67	0.94±0.03	
Bayesian	2	89.72±8.94	100.0±0.00	0.94±0.05	
	3	88.17±11.26	100.0±0.00	0.93±0.07	
Empirical		72.95±14.27	100.0±0.00	0.84±0.09	0.7

Impact of Aborting Deserialization Early



Digging Into False Positives

After manual review, all the false positives fall into one of these categories:

- Java Transaction API
- Networking
- Instrumentation
- Remote Method Invocation (RMI)
- Managed Bean

which indeed look like attractive targets for deserialization attacks.

Thank you

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