

Offensive AI

A fun and not (so) explored field mixing **offensive cybersecurity** and
machine learning.



About Me!

Dorian Bachelot

Research Engineer

*@LHS/CentraleSupélec/INRIA
#Malware Developer/Detection*

<https://dorianb.net>



Introduction

AI, ML, DL, OAI...

Field Overview

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Definition

Offensive artificial intelligence (OAI) can be defined as the field in which artificial intelligence algorithms or models are used to **automate one or multiple parts of an offensive security task**.

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This cover:

- Vulnerability scanning
 - Exploit automation
 - Attack path identification
 - ...

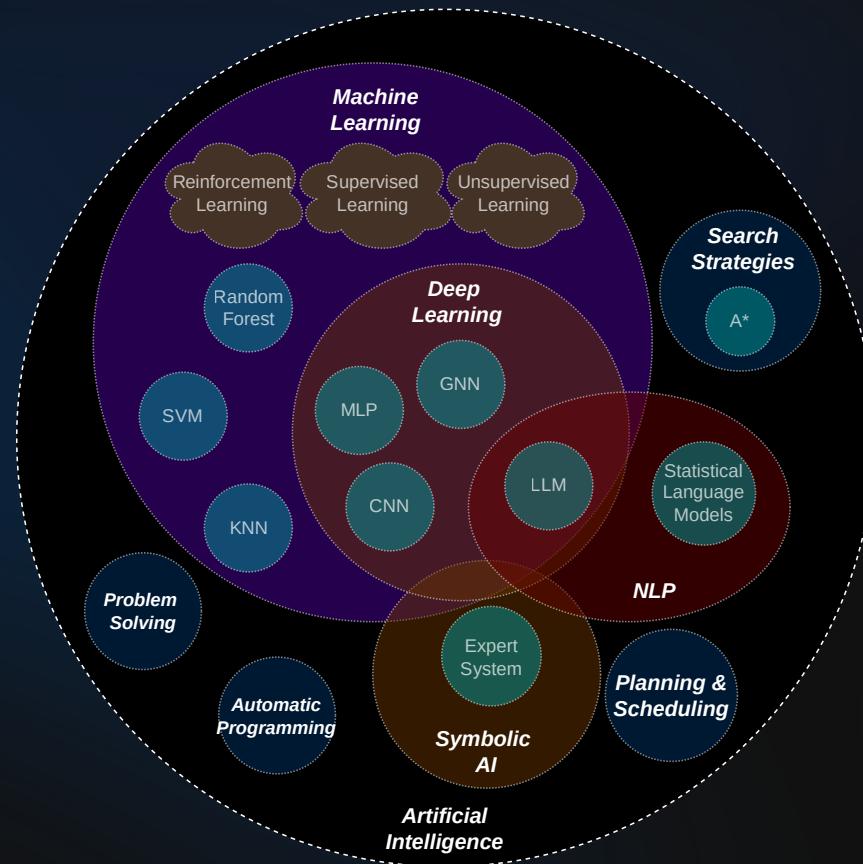
Reminder on AI

Reminder on AI

We can classify as AI any system that solves a problem or achieve a goal and have some degree of adaptation and autonomy.

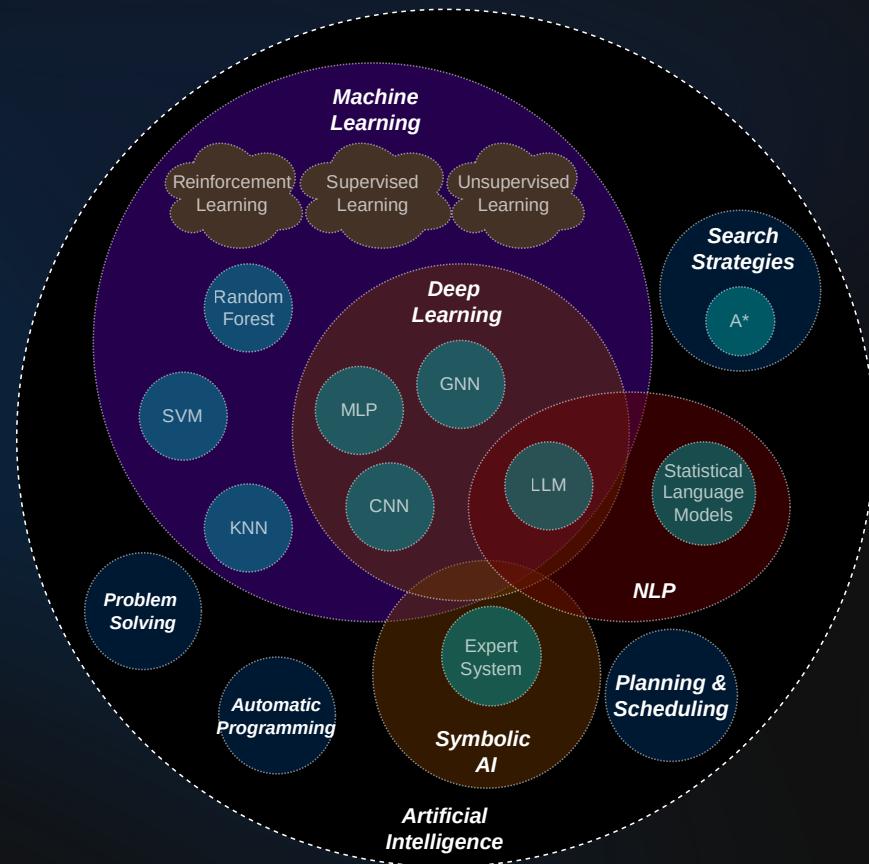
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Machine Learning ≠ AI ≠ Deep Learning ≠ LLMs

OAI

Global overview

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OAI for C2 Piloting

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OAI for Evasion

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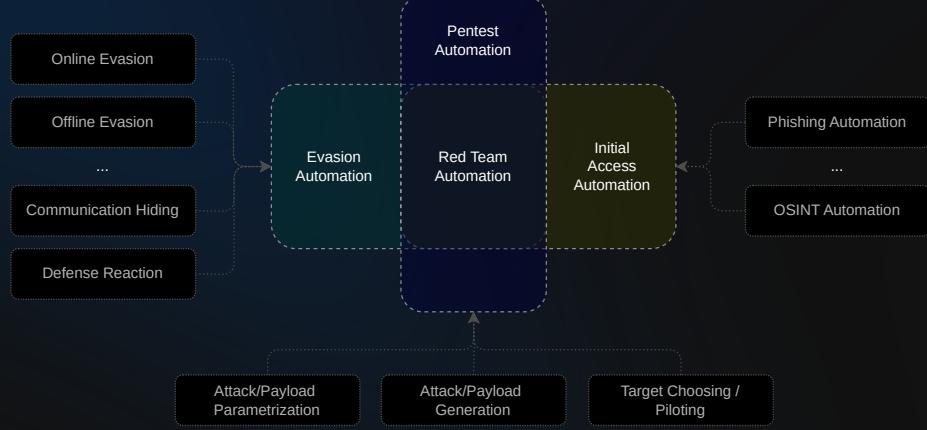
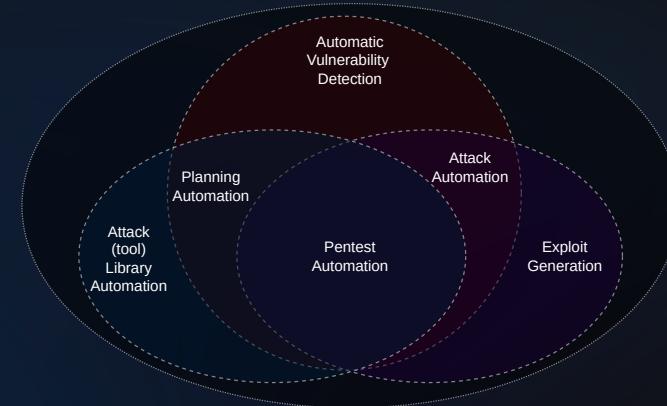
Overview

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OAI can also be cut in **multiple subfields**, which correlate closely to some **use cases** like **pentest** or **red team automation**.

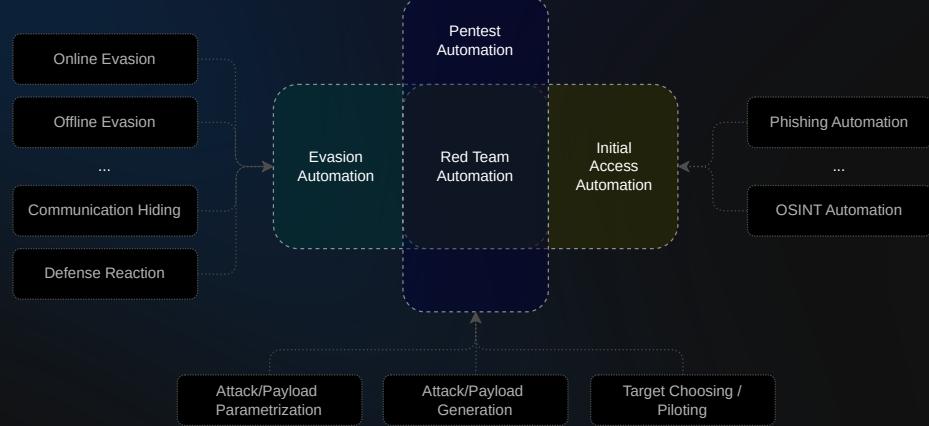
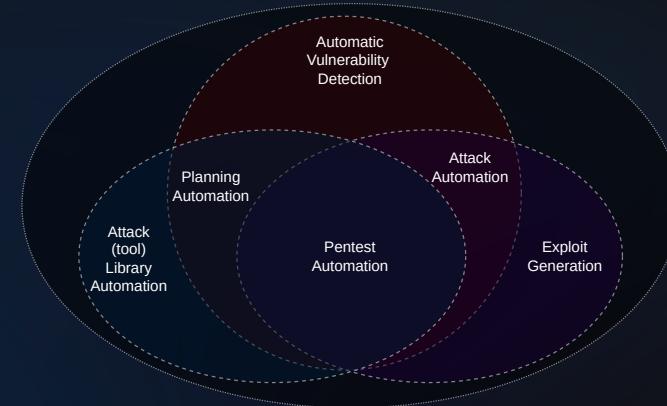
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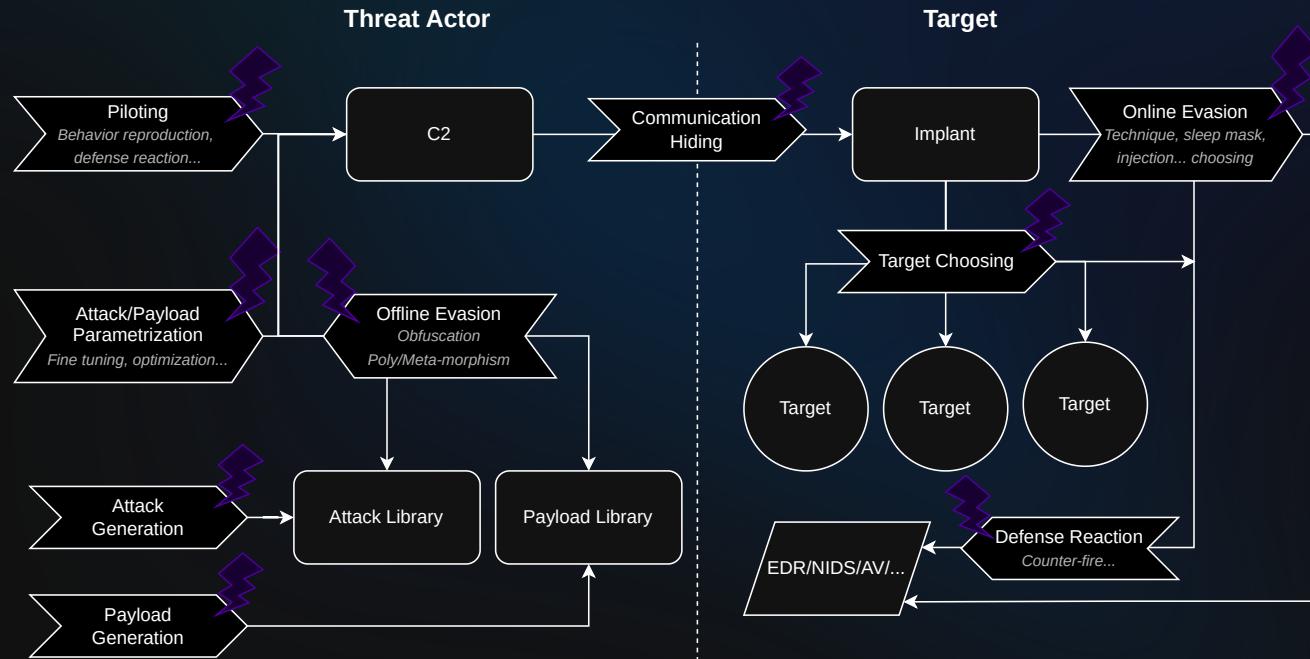
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Automation ≠ Better than Humans

The different subfields

The different subfields



OAI for C2 Piloting

Target choosing, attack choosing...

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C2 Piloting

C2 Piloting

What is a C2?

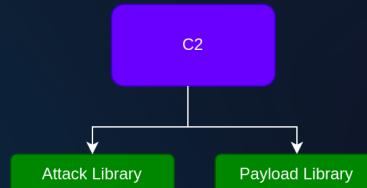
- Pilot implants, that have infected some hosts.
- Implants can communicate directly with the C2, or can do it **through another implant**.
- Can issue commands, and **send attacks** (modules).
- Focus on **evasion**, hiding communication and using advanced implants.
- Used to **pivot** and **deeply infect** a network.
- Controlled by an operator (or AI!).

C2 Piloting

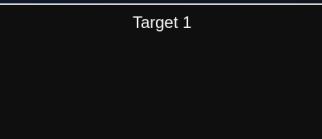
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Threat Actor



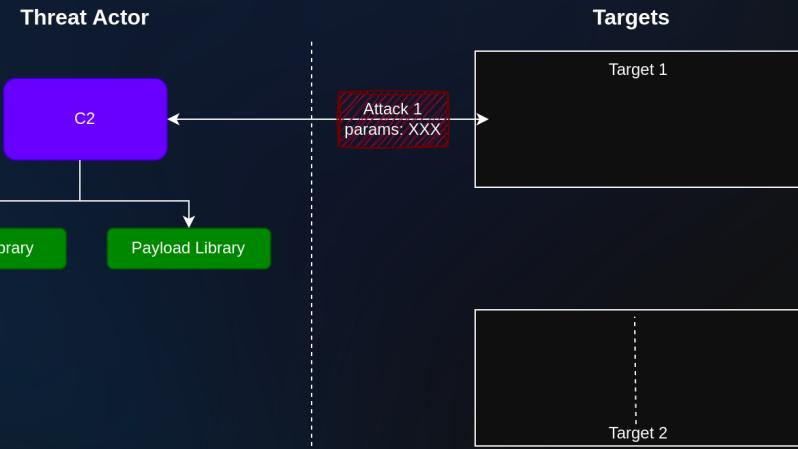
Targets



C2 Piloting

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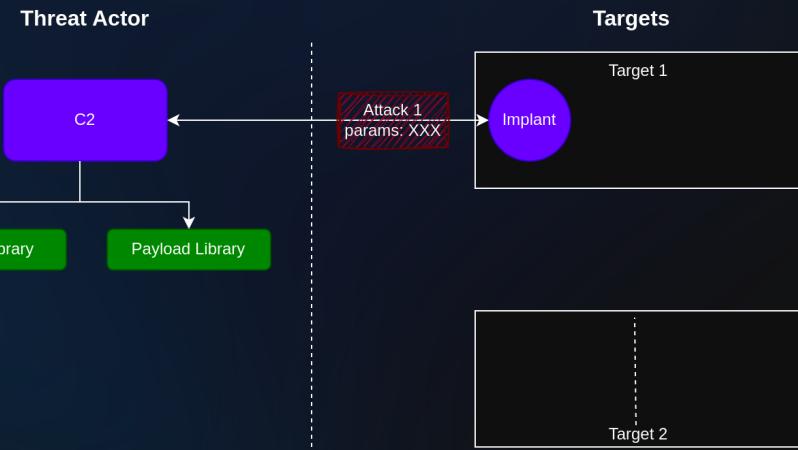
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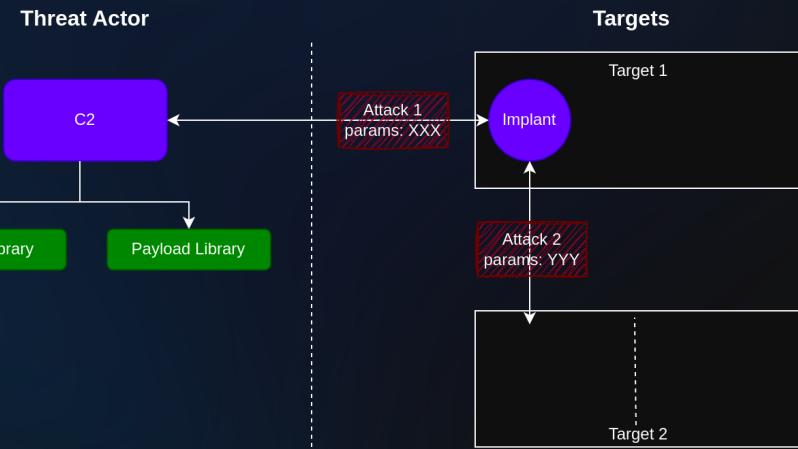
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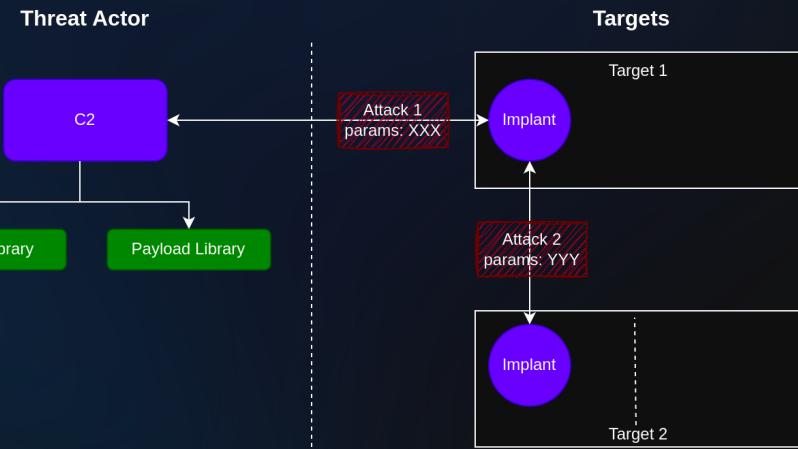
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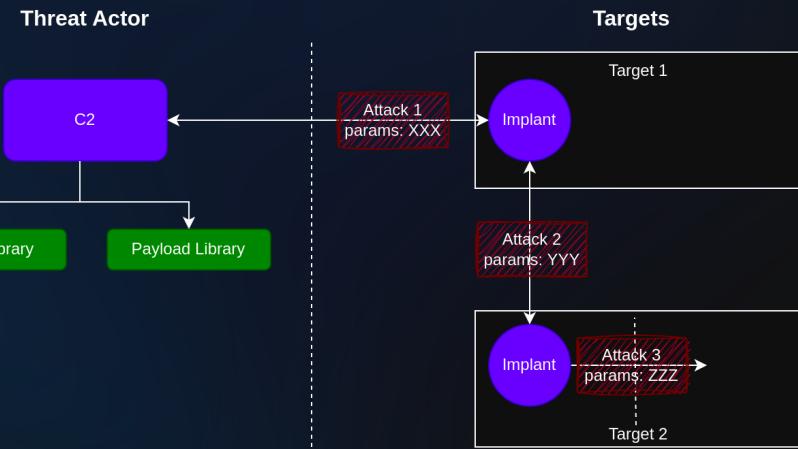
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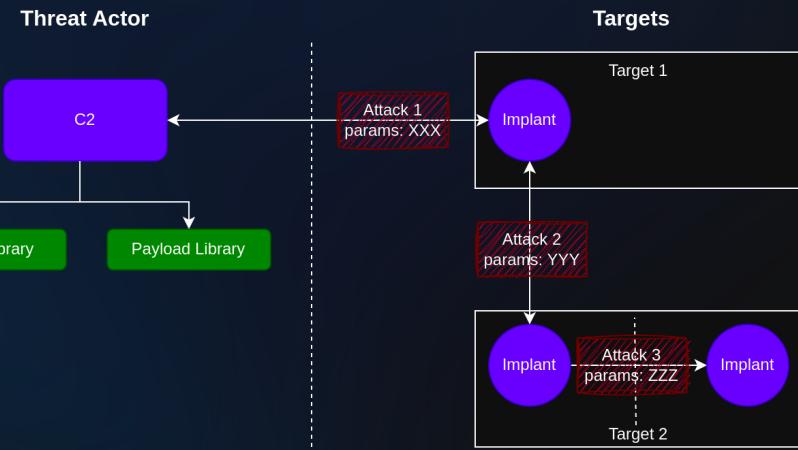
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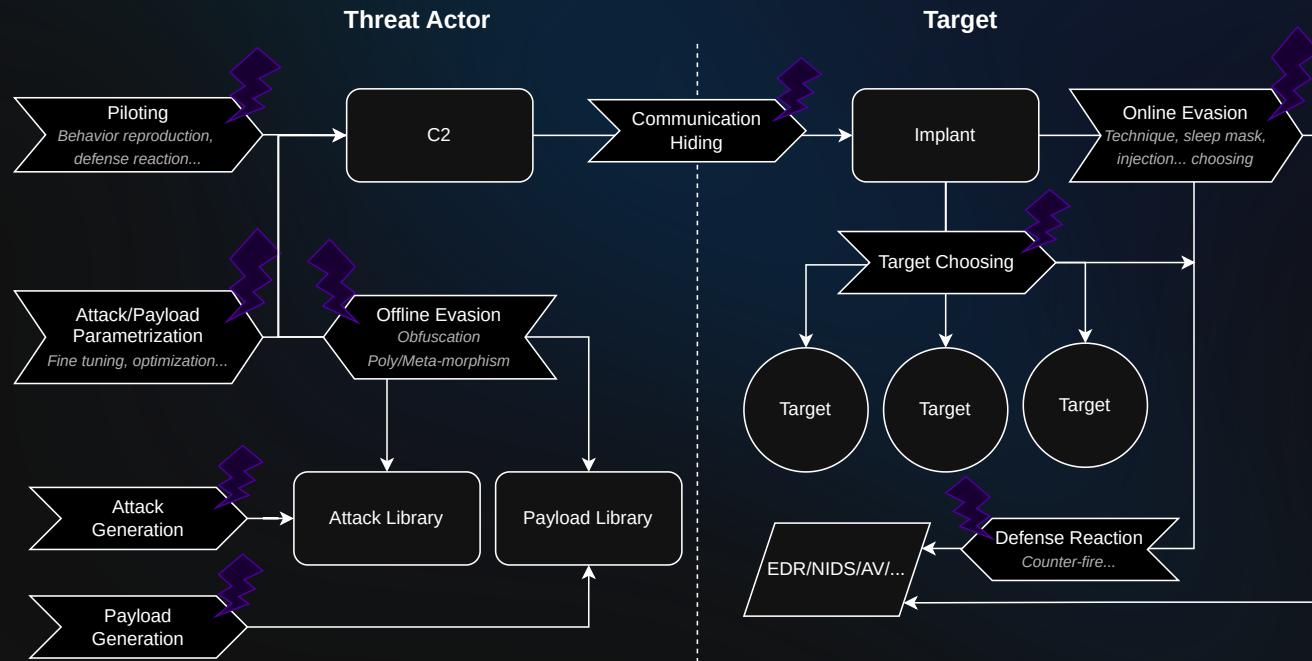
C2 Piloting / The Idea

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Consists of selecting a target, an attack and parameters using a model/algorithm.

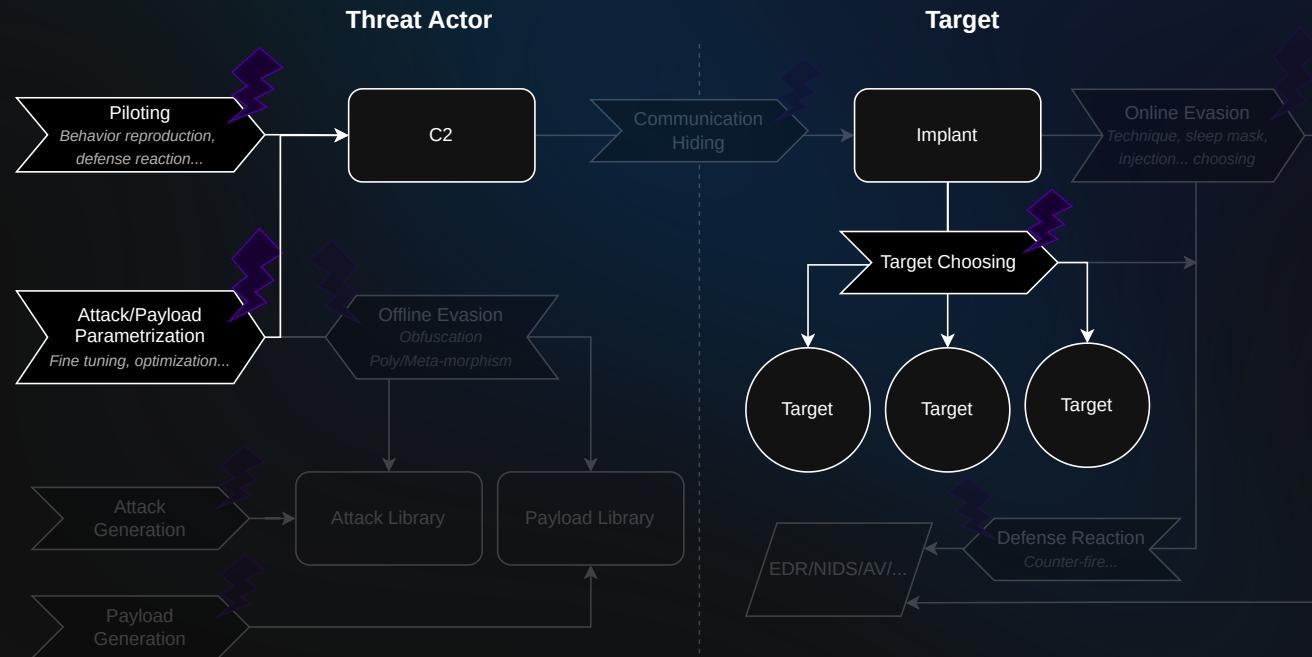
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Recipe:

- Take a **C2 with an API** (giving automation power on ALL operations).
- Prepare an **attack library** (modules), with exposed parameters.
- Add some model/algorithm.
- Shake. Done!

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(@chrisrohlf)

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Not that simple in reality... A lot of AI-related issues.

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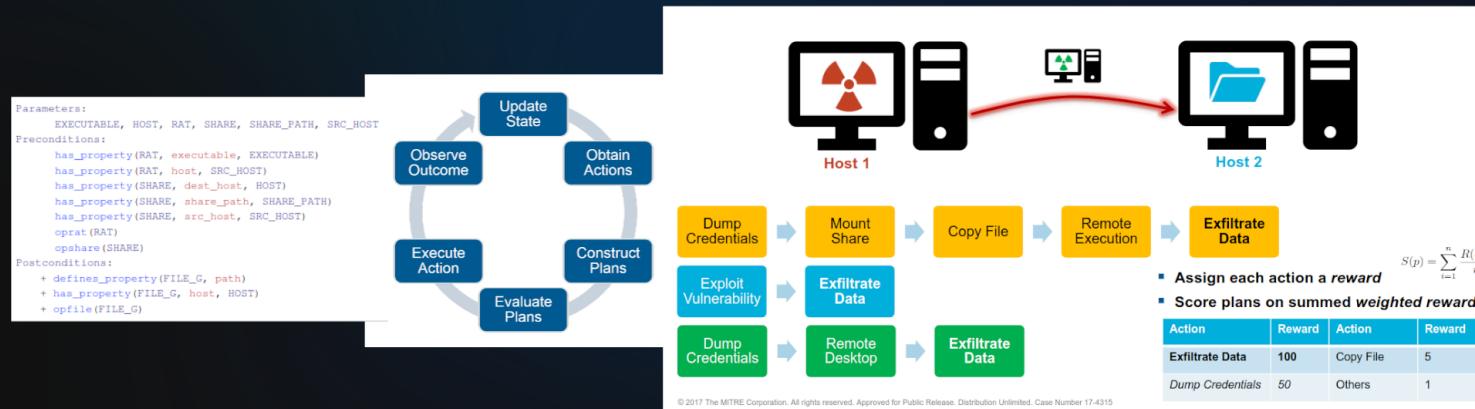
C2 Piloting / Heuristics

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Caldera⁽¹⁾, an automated framework for adversary emulation (by Mitre), rely on a **heuristic** to select attacks & targets.

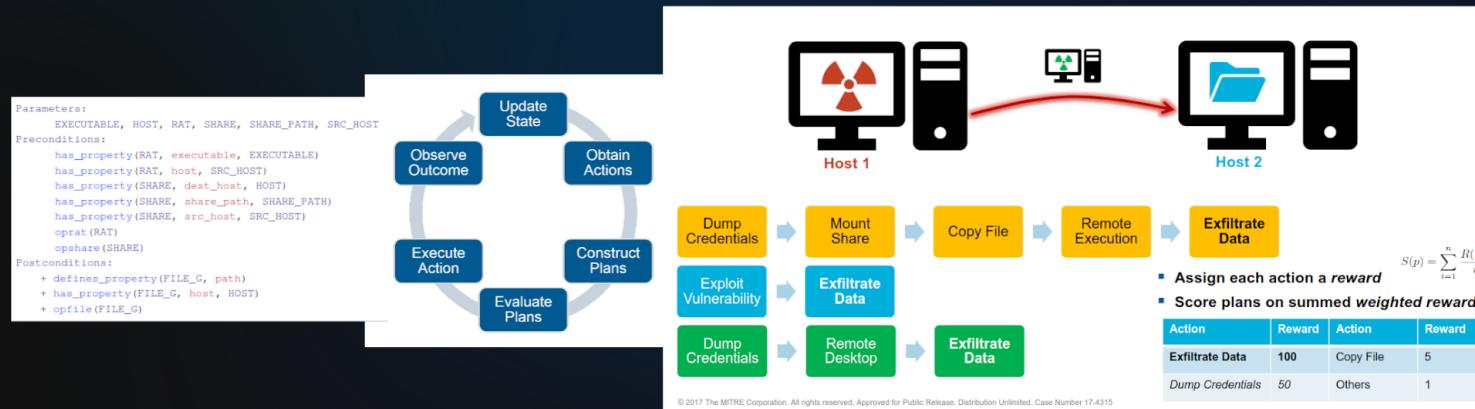
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Based on pre & post conditions, really basic and not very "smart" system.

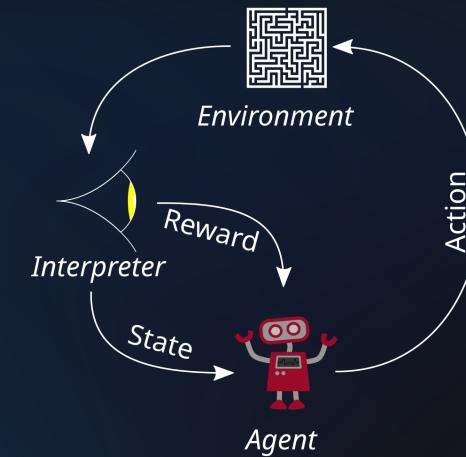
C2 Piloting / RL

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C2 Piloting / RL

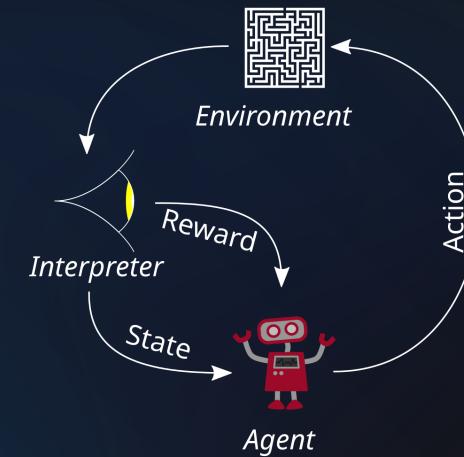
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- S is the set of all states,
- A is the set of all actions,
- $R : S \times A \times S \rightarrow \mathbb{R}$ is the reward function,
- For a step k , $r_k = R(s_k, a_k, s_{k+1})$ is the associated reward function,

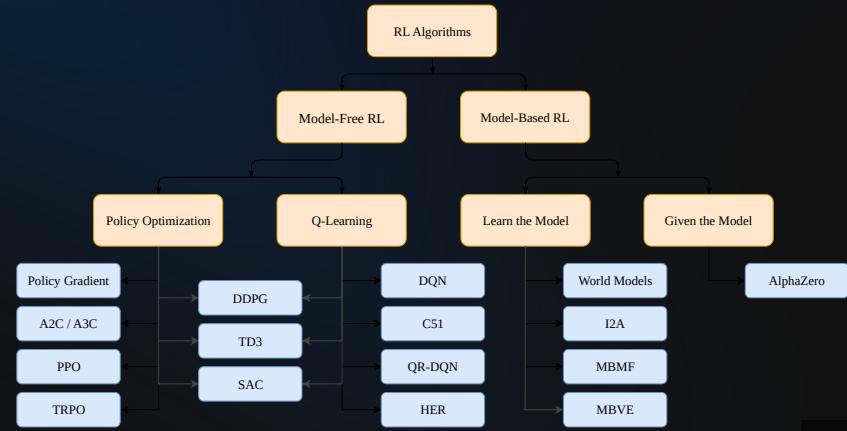
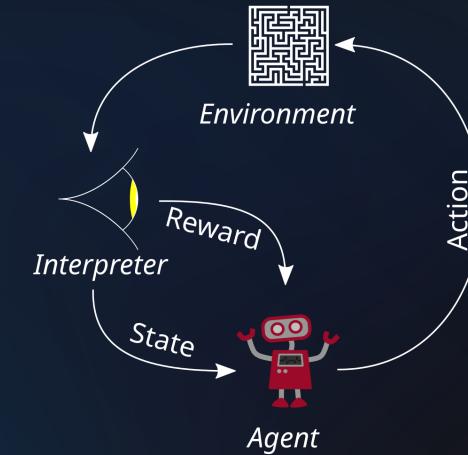


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Reinforcement learning is vast:



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C2 Piloting / RL for Piloting

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RL fit well for C2 piloting:

- S contains all network states (like machines, OSes, open ports...),
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- R is possible to construct, has demonstrated with Caldera's heuristic (**not that easy...**).

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Playing with R make it possible to complexify model behavior (e.g., valorize exploration vs exploitation, take defense into consideration...)

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C2 Piloting / RL Environment

C2 Piloting / RL Environment

First issue, to use RL you need a training environment that'll simulate (mock) inputs/outputs ⁽²⁾⁽³⁾. This is called a simulation environment (or Gym).

Multiple environments are available, but are globally oriented toward Deep Learning, making them **very basic**:

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(1, 0)	True	True	True	0.0	1.0	False	False	False	False	False	True	True	False
(3, 1)	False	True	True	0.0	0.0	False	False	False	False	False	False	False	False
(3, 0)	True	True	True	100.0	2.0	False	False	True	True	True	False	False	True
(4, 1)	False	True	True	0.0	0.0	False	False	False	False	False	False	False	False
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(3)

Most, if not all, are **oversimplifying** the problem, and some doesn't even provide realistic evaluation (emulation, or running in a real IS). For example, none allow **attack parametrisation**. And most are using a probability of failure per action (artificial realism).

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C2 Piloting / Some RL Environments

C2 Piloting / Some RL Environments

Name	Release Date	Features
NASim	2019	Simulation only
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Metasploit is the **ONLY** used C2 across the literature.

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C2 Piloting / More RL Agents

C2 Piloting / More RL Agents

Model	Technique	Complex Behavior	Parametrisation	Generalization	Year
POMDP ⁽⁴⁾	POMDP	No	No	No	2013
LD-PenTesting ⁽⁵⁾	POMDP	~Defender Behaviour	No	No	2020
EPPTA ⁽⁶⁾	POMDP + PPO	No	No	No	2023
AutoRed ⁽⁷⁾	POMDP	No	No	GNN	2024

C2 Piloting / More RL Agents

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Multiple issues with these approaches :

- Questionable generalization (except AutoRed),
 - Imperfect reward function R /policy π (complexity),
 - No attack parametrisation,
 - Questionable performances,
 - Low quality/high abstraction environments.

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C2 Piloting / A Complex Problem

C2 Piloting / A Complex Problem

Multiple questions:

- **One or multiple** models to select the target, the attack and the parameters?
- Does the target selection model **see the whole network**, or just select the target with the best attack?
- Since a network can have a (virtually) **infinite number of machines** (targets), how to construct the input/context for the target selection model?
- How to create an adequate **reward function/policy**?
- How to capture the **complexity** of the problem (like taking into account defense reaction)?
- C2 Piloting is a **planning problem** (with goals & subgoals)?
- On a big network, with a lot of possible actions, each with many parameters, how **not to collapse**?

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C2 Piloting / New Approach

C2 Piloting / New Approach

Proposed approach

Issue	Solution	Description
Generalization	GNN / Carrousel	Ingest the network context independently from its size. Learn to retain only interesting information. Context-based ingestion.
Partially Observable	POMDP + Dreamer (<i>JEPAs</i>)	Internal environment representation, latent space reasoning.
Complex Behavior	Complex <i>R</i> & Goals	Complexify the reward function. Add goals & subgoals to complexify policies (planning).
C2 Automation	New Specific C2	Create a C2 with automation in mind.
RL Environment	New Emulation First RL Environment	Create a new RL environment centered around emulation (maximum realism).

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C2 Piloting / Other Approaches

C2 Piloting / Other Approaches

Other approaches exist:

- Some people are trying to use **LLMs for C2 piloting** (me! ⁽⁸⁾), but also end-to-end OAI. Results are not great, OAI is not really **hallucination-compatible** (e.g., commands needs to be exact, IPs also, impact if the wrong target...).
- RL is not the only learning method: **Self-Supervised Learning** is trending.
- **Heuristics** are not dead.
- **Expert systems** (analogy to the defensive side) should also be explored.

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The dream is to have **end-to-end OAI** (target, attack, parameters choosing with attack generation).

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C2 Piloting / Conclusion

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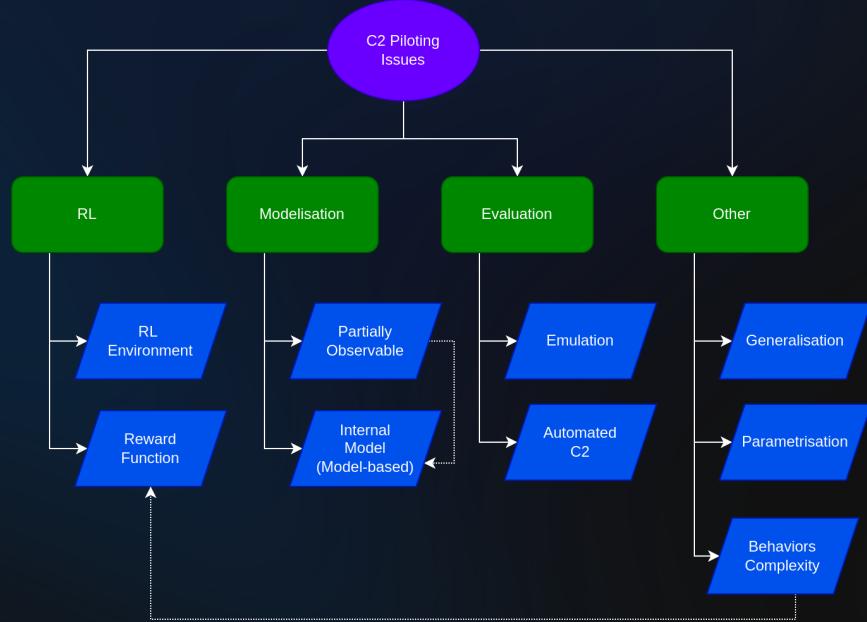
Some "Hot Takes":

- C2 Piloting is **hard**.
- This is not just a **model choice issue**.
- Past literature (minus some exception) are
focusing on the wrong problematic.
- Linked **use cases** are huge.
- Ask many **fundamental** questions.
- When it will work, the **impact might be important**
for defenses.
- *(LLMs are not the solution)*

C2 Piloting / Conclusion

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OAI for Evasion

Online & Offline evasion...

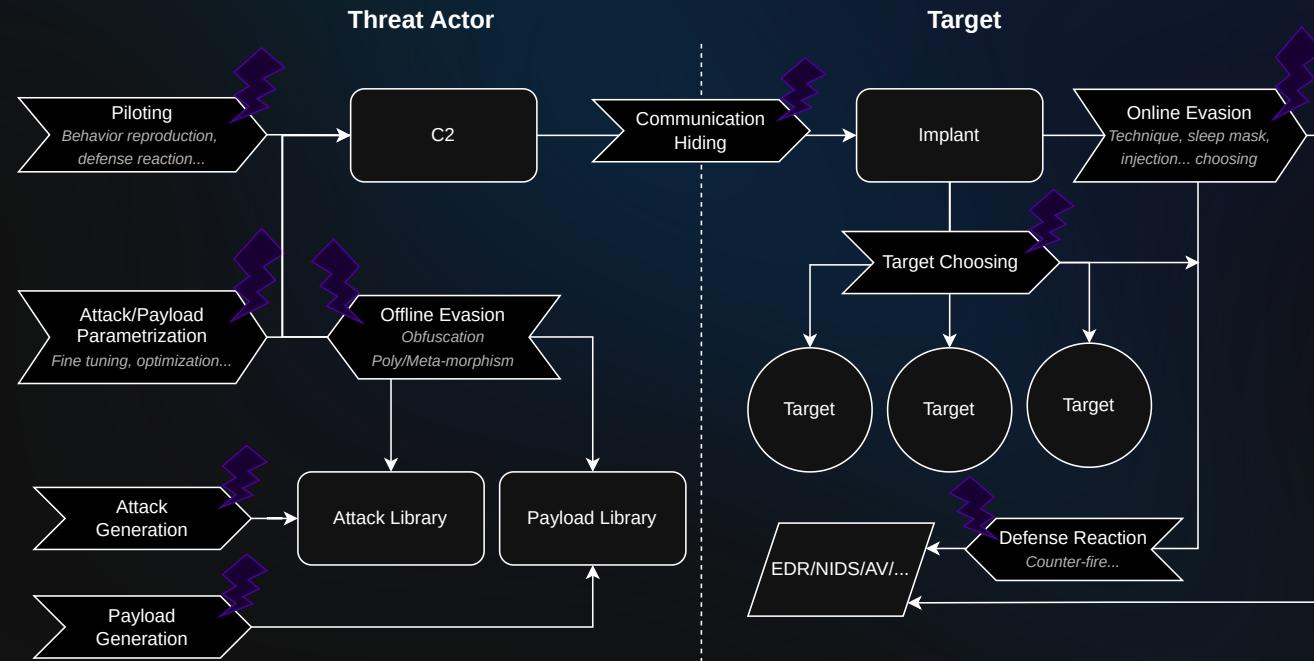
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Consists of **optimizing** (e.g., by selecting parameters) an evasion method.

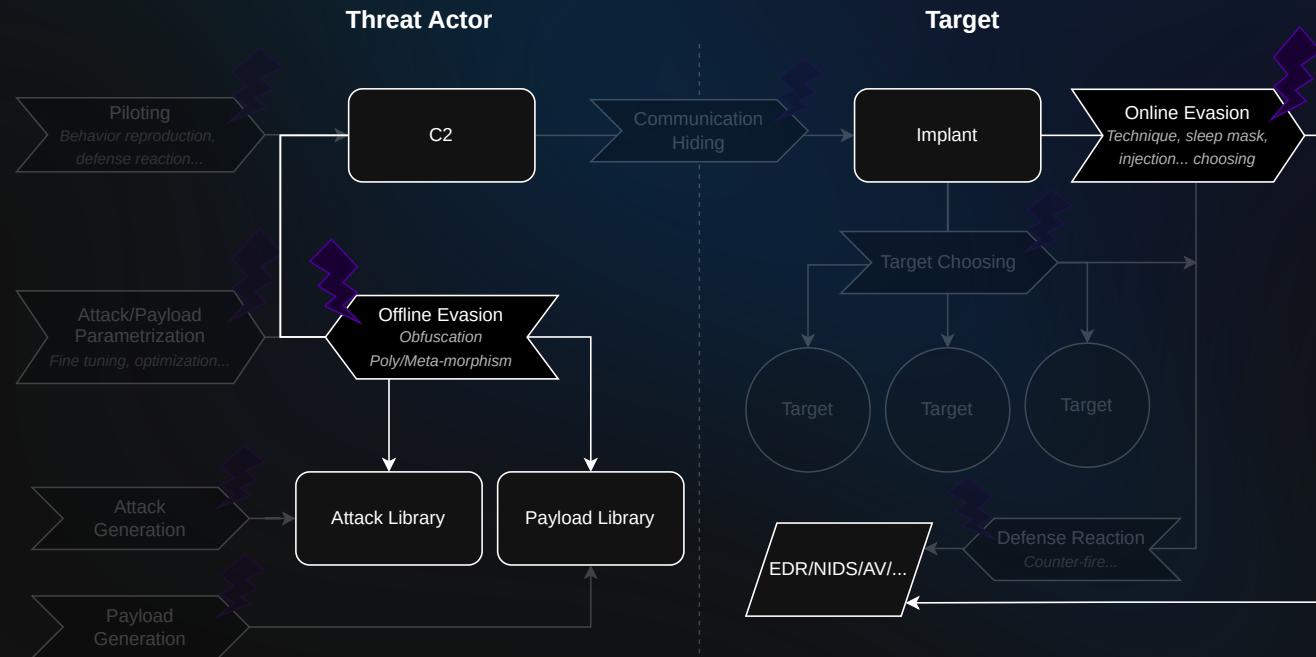
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Evasion / The Idea

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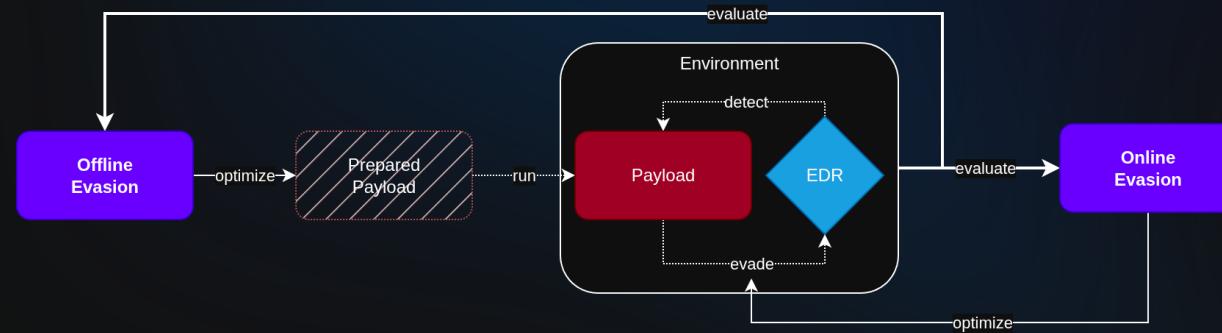
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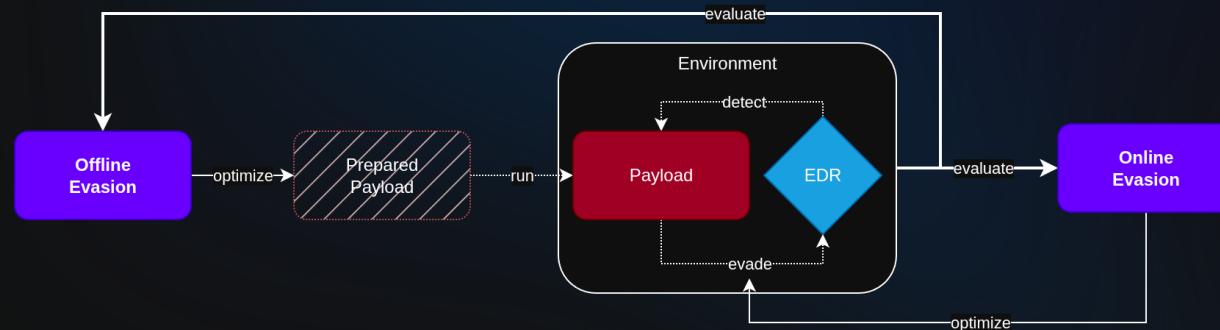


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Each sensor is generally **more vulnerable** to specific combination of evasion techniques, associated with specific parameters.



AI can be used to find these combinations and associated parameters, **optimizing evasion**.

Offline Evasion

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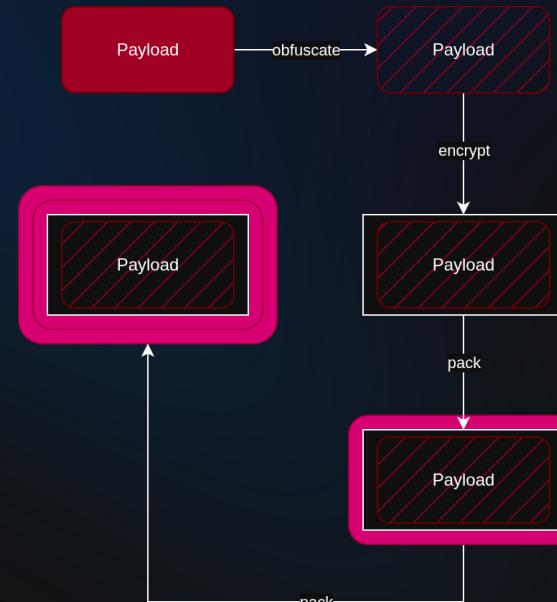
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Objective: Complexify part of a binary to make detection and/or reverse engineering harder. This maintains same functionalities, but make analysis more difficult.

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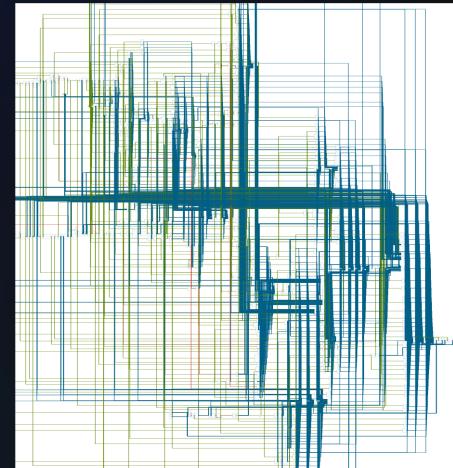
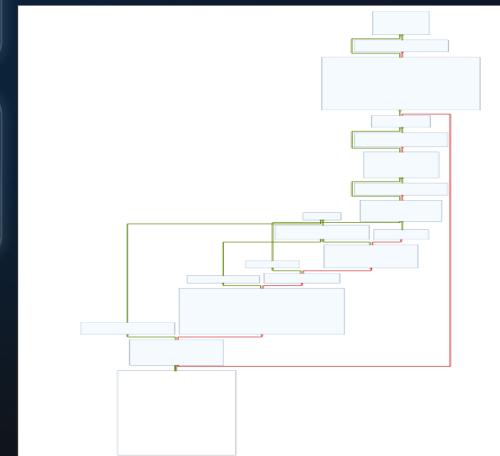
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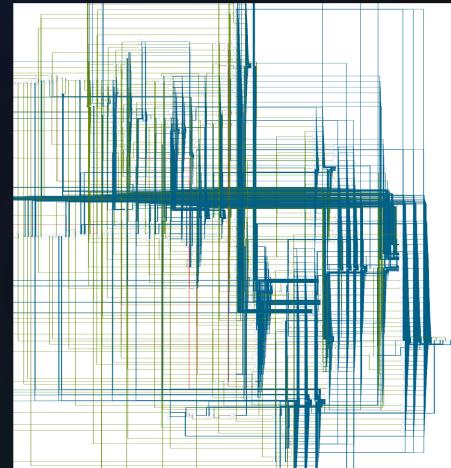
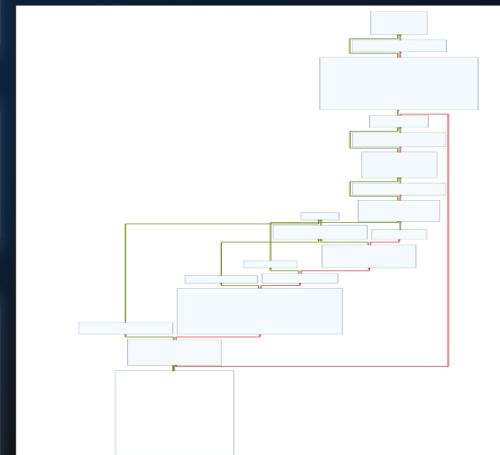
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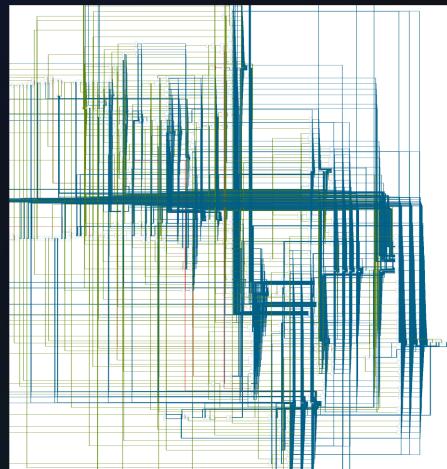
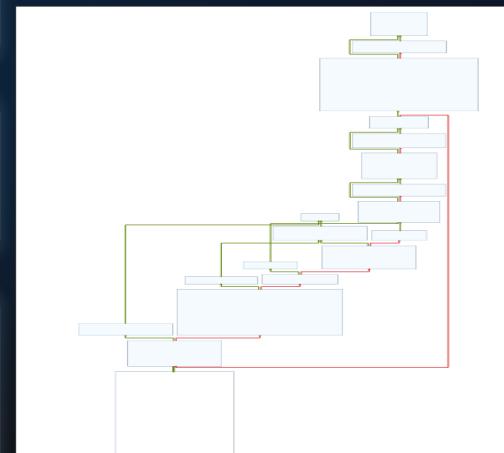
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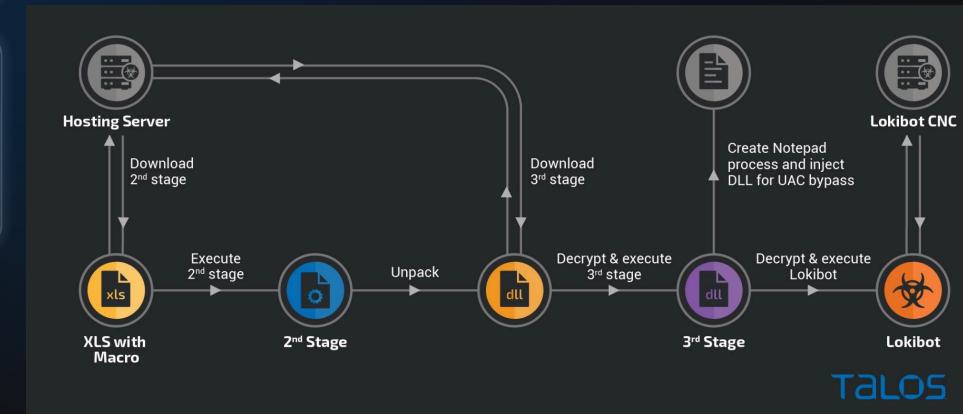
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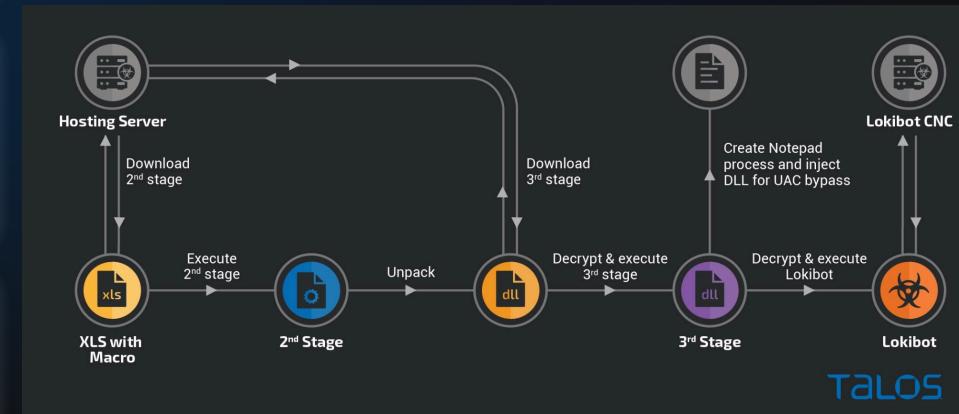
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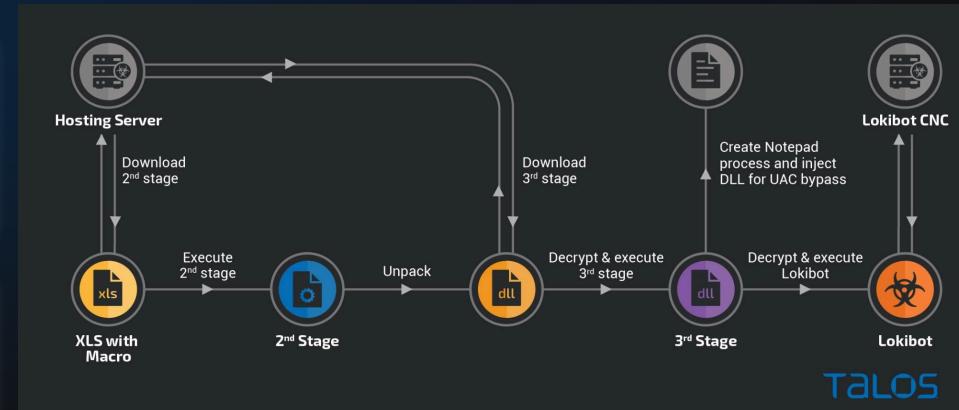
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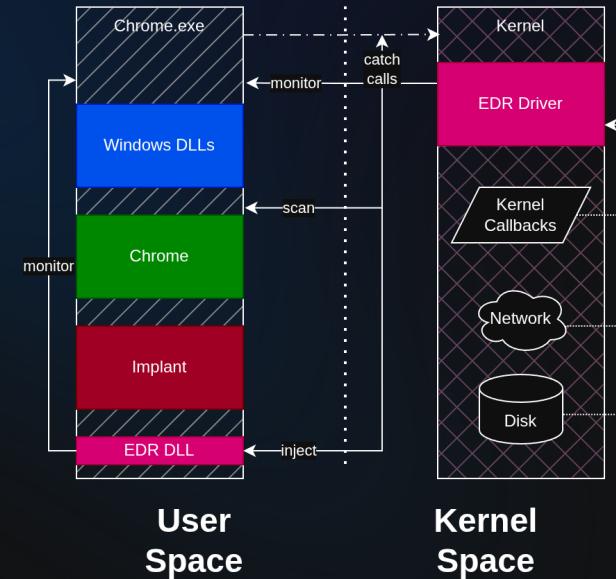
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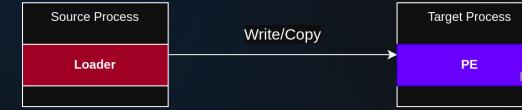
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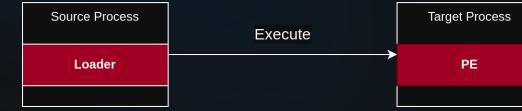
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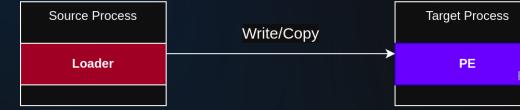
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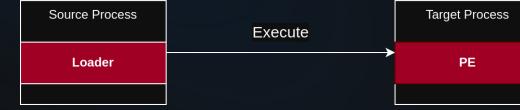
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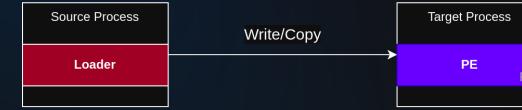
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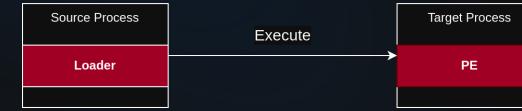
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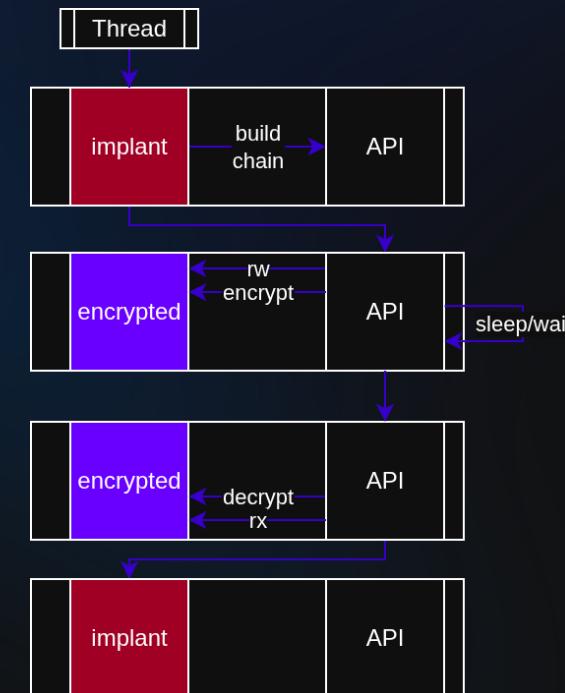
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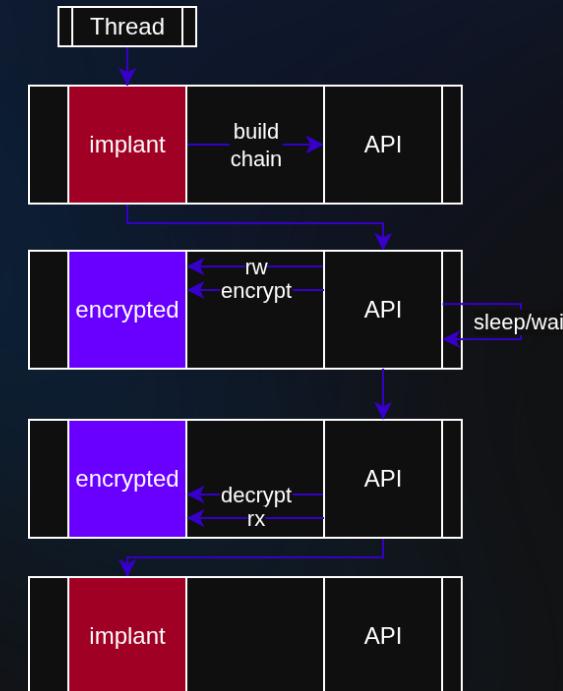
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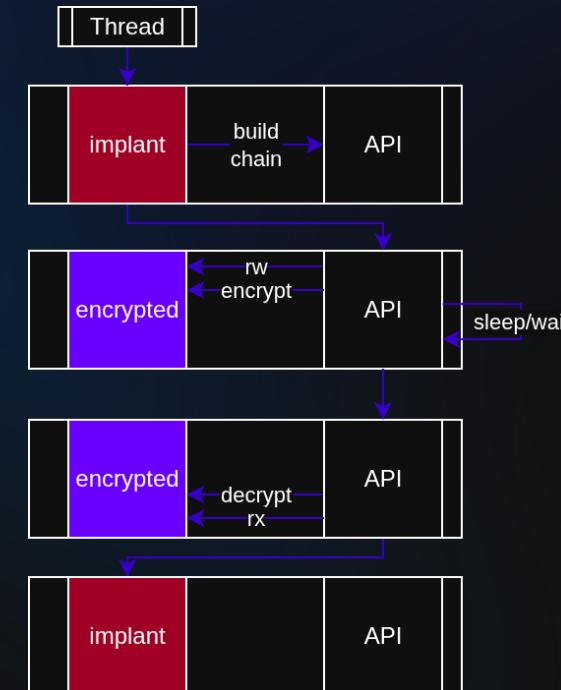
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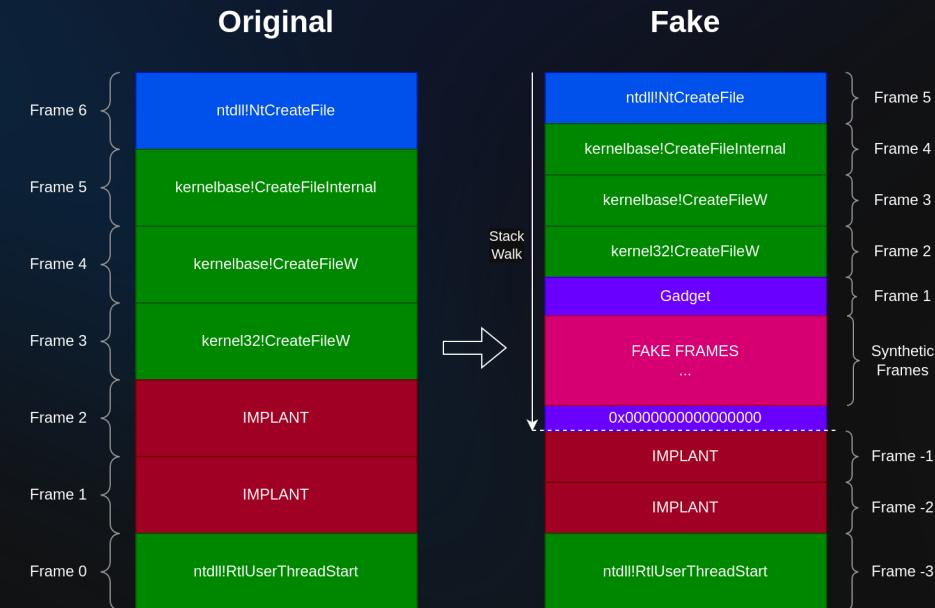
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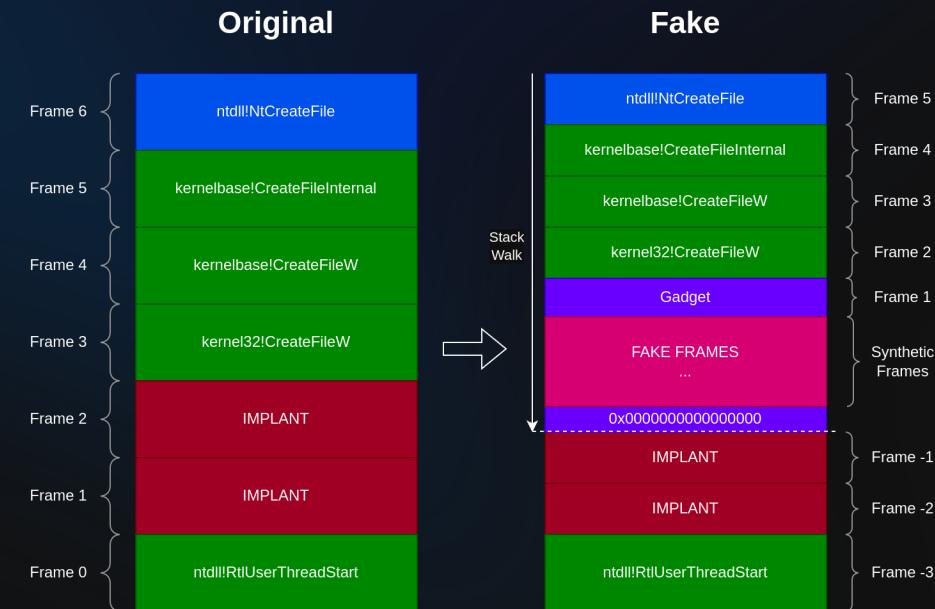
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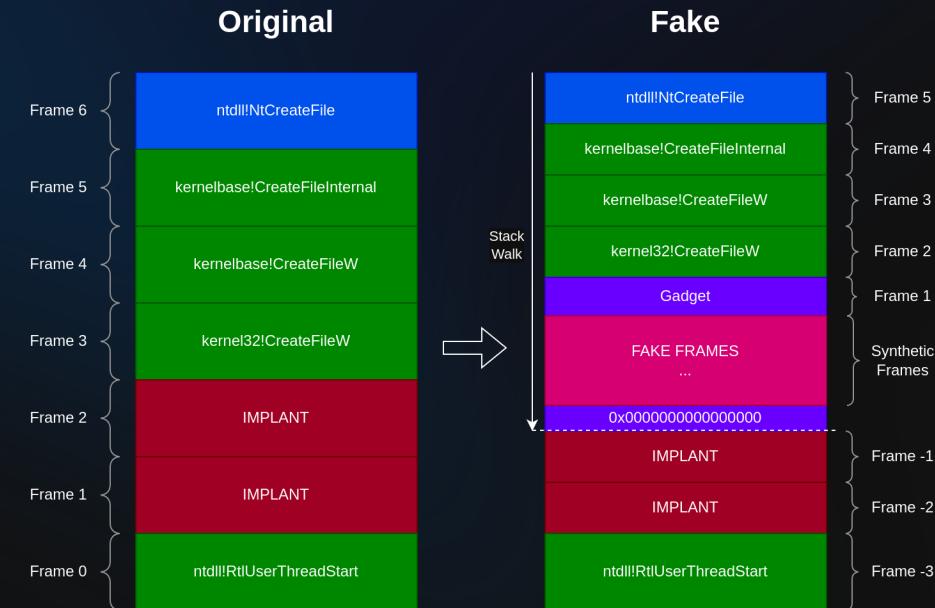
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OAI for Evasion

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Product	Call Stack	Process Injection	Metamorphism	Memory Masking
EDR1	Variant 2	"Explorer"	Variant 1	X
EDR2	Variant 2	X	Variant 1	X
EDR2 + Win11	Variant 3	"Google Chrome"	X	Variant 2

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OAI for Evasion

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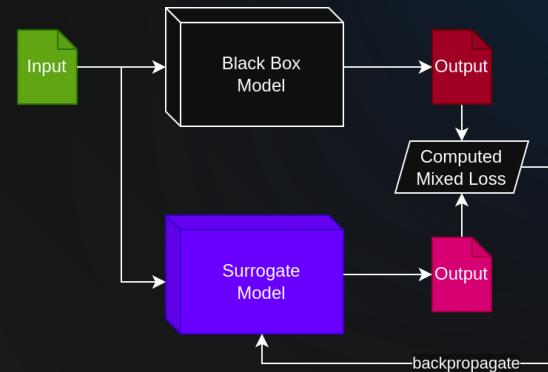
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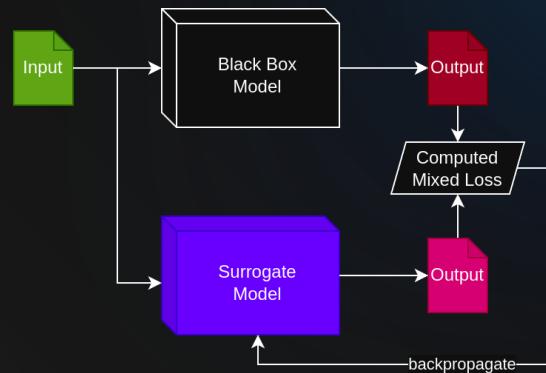
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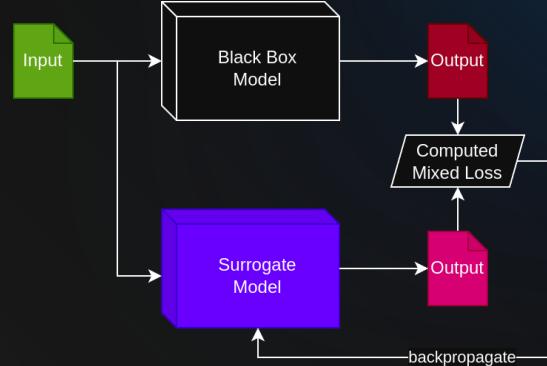
We can then use the surrogate model to build adversarial inputs to force misclassification by the black box model. For that, we can use the surrogate model internals (like embedding or gradients).



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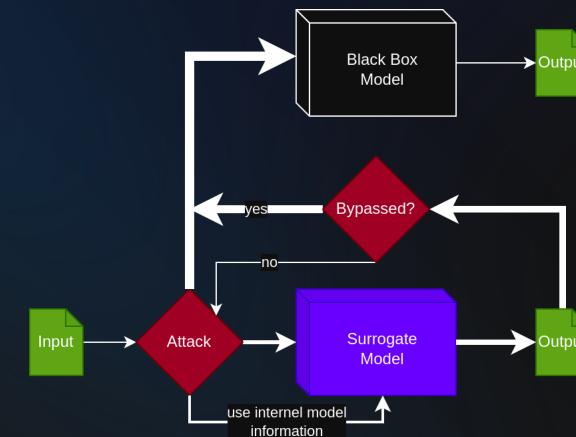
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OAI for Evasion

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Conclusion

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Surrogate Model: Evasion

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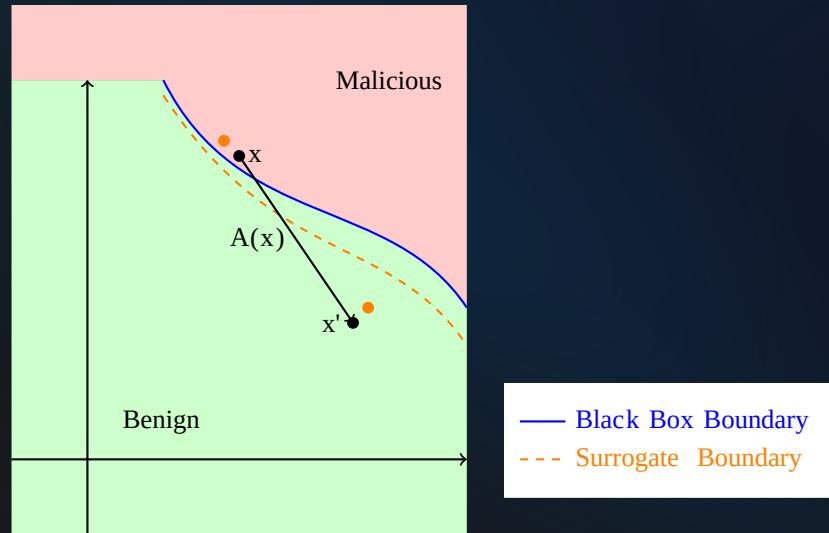
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Possible attacks

- Add obfuscation, packing...
- Use process injection, call stack spoofing...
- Mask/Obfuscate memory...

All of these techniques are primitives that we can leverage to build adversarial binaries, using our surrogate model.

Surrogate Model: Visualization



Where $A(x) = \epsilon_\Omega(x)$.

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OAI for Evasion

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Conclusion

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Some "Hot Takes":

- Automation for evasion is **easier** than C2 piloting.
- Not much literature on the subject.
- Might not be explored by anyone?
- Multimodal > Unimodal
- Linked **use cases** are important.
- When it will work, the **impact might be important** for defenses.
- *(LLMs are not the solution)*

Conclusion

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 - OAI for phishing.
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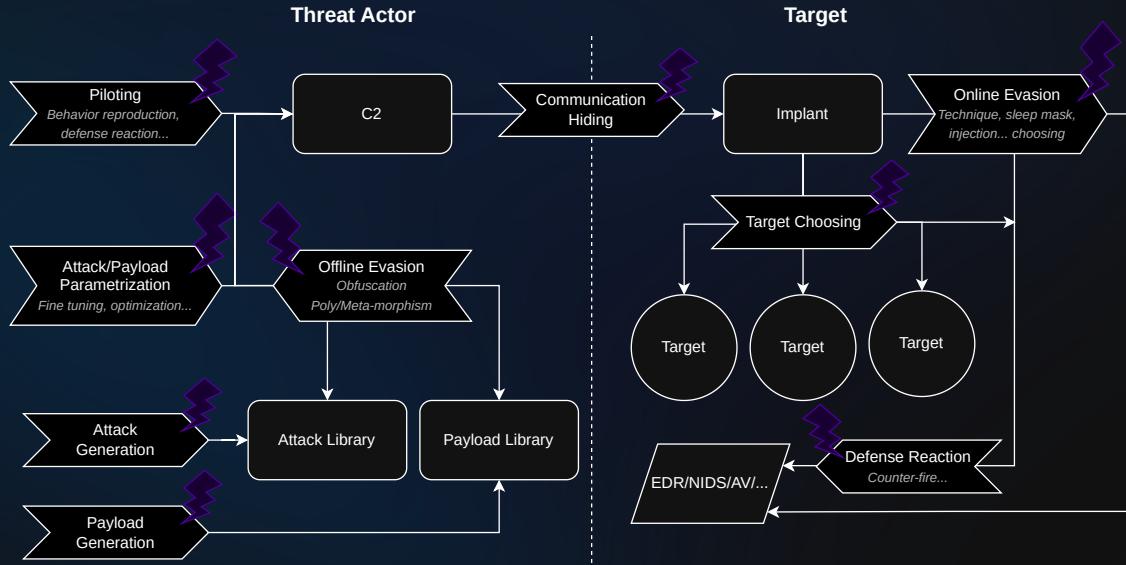
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Thanks!

A complete version of this conference is available here [] <https://dorianb.net/Talks/OAI2026/Full>

For more <https://dorianb.net/>

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