secml-malware: Pentesting Windows Malware Classifiers with Adversarial EXEmples in Python

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Abstract
Machine learning has been increasingly used as a first line of defense for Windows malware detection. However, recent work has shown that these detectors can be evaded by adversarial EXEmples, carefully-perturbed input malware samples, thus demanding for tools that can ease and automate the adversarial robustness evaluation of such detectors. Thus, we present secml-malware, the first Python library for computing adversarial attacks on Windows malware detectors. secml-malware implements state-of-the-art white-box and black-box attacks on Windows malware classifiers, leveraging a set of manipulations that can be applied to Windows programs while preserving their functionality. The library can be used to perform the penetration testing and assessment of the adversarial robustness of Windows malware detectors, and it can be easily extended to include novel attack strategies. Our library is available at https://github.com/pralab/secml_malware.

Keywords: Python, Windows, malware, programs, adversarial, machine learning

1. Introduction
Machine learning is extensively used as a first line of defence against the spread of Windows malware. Both industry and academia are developing increasingly-sophisticated algorithms for extracting malicious patterns from data, leveraging different feature sets and model architectures (Raff et al., 2018; Coull and Gardner, 2019; Saxe and Berlin, 2015; Anderson and Roth, 2018). Meanwhile, recent work has shown that these learning-based malware detectors can be misled, enabling the attacker to infect the target device with malware (Demetrio et al., 2019, 2021, 2020; Kreuk et al., 2018; Suciu et al., 2019; Sharif et al., 2019; Anderson et al., 2017; Castro et al., 2019). The latter can be achieved by applying practical manipulations that do not alter the functionality of a malicious program, but rather its file structure. In this way, the attacker crafts an adversarial EXEmple, i.e., an adversarial example for Windows malware detectors (Demetrio et al., 2021), which can be run on the target machine even after being manipulated. Hence, there is the need of open-source tools to test classifiers and defenses against these threats, in order to understand how to mitigate such them, while being one-step ahead of possible attackers.

For this reason, we propose secml-malware, the first Python library for creating adversarial EXEmples in input space, providing developers and analysts a tool for performing security evaluations on their machine-learning Windows malware detectors. The library implements most of the proposed practical manipulations to perturb Windows programs, and it is written on top of the secml library (Pintor et al., 2022). The structure is modular enough
Table 1: Attacks implemented in \texttt{secml-malware}, along with the manipulations they apply.

| Proposed by | Practical manipulation |
|-------------|------------------------|
| Demetrio et al. (2019) | partial dos |
| Demetrio et al. (2021) | full dos |
| Demetrio et al. (2021) | extend |
| Demetrio et al. (2021) | shift |
| Kolosnjaji et al. (2018) | padding |
| Kreuk et al. (2018) | slack+padding |
| Suciu et al. (2019) | slack+padding |

| Proposed by | Practical manipulation |
|-------------|------------------------|
| Demetrio et al. (2020) | GAMMA padding |
| Demetrio et al. (2020) | GAMMA section inj. |
| Demetrio et al. (2021) | partial dos |
| Demetrio et al. (2021) | full dos |
| Demetrio et al. (2021) | extend |
| Demetrio et al. (2021) | shift |
| Demetrio et al. (2021) | padding |
| Demetrio et al. (2021) | slack+padding |

2. \texttt{secml-malware}: Architecture and Implementation

The library is divided in three main modules: \texttt{attack}, \texttt{models}, and \texttt{utils}. Each of these packages is provided with unit tests that asserts the correct behaviour of these techniques.

\textbf{The attack module.} This module contains all the attacking strategies, divided in \texttt{whitebox} and \texttt{blackbox} modules, and we provide a complete list of them in Table 1. Attacks inside the \texttt{whitebox} sub-module are implemented by leveraging practical manipulations that address the perturbing of single bytes inside the program (Demetrio et al., 2019, 2021; Kreuk et al., 2018; Suciu et al., 2019). These attacks exploit the ambiguity of the file format, by filling unused space inside the binary or injecting new content in particular positions, but always preserving the original functionality of the sample. Since we use \texttt{secml}, the optimizer uses \texttt{pytorch} (Paszke et al., 2019), and all the gradient computations leverage this framework. Attacks inside the \texttt{blackbox} sub-module are implemented using DEAP (Fortin et al., 2012), a library for encoding genetic optimizers, and they span from byte-based to more structural manipulations, e.g. section and API injection (Demetrio et al. (2020, 2021)). We also include GAMMA (Demetrio et al., 2020), that is a black-box attack leveraging the injection of benign content to fool the target detector, by also keeping low the size of the adversarial malware and the number of queries sent. Since we use \texttt{secml}, the optimizer leverage the \texttt{pytorch} framework (Paszke et al., 2019) for computing gradients.

\textbf{The models module.} This sub-module hosts the definition of two state-of-the-art classifiers: a deep neural network, called \textsl{MalConv} (Raff et al., 2018), and a Gradient Boost Decision Tree (GBDT) (Anderson and Roth, 2018). Both of them are encapsulated in classes that can be passed to the underlying \texttt{secml} framework for computing the attacks.

\footnote{1. \url{https://github.com/pralab/toucanstrike}}
The latter is modular enough for including most models from different frameworks, and the end user can leverage this feature to include their custom target.

**The utils module.** This sub-module contains support code to implement practical manipulations, such as functions for keeping the constraints intact.

Lastly, we also provide a detailed description on how to create a custom conda environment and a Docker container.

### 3. Application Example: Evaluating Adversarial Robustness of MalConv

To show the potential of our library, we apply both white-box and black-box state-of-the-art attacks already coded in secml-malware against a deep neural network called MalConv (Raff et al., 2018). The latter is just an example we chose for simplicity, but secml-malware provides wrappings also for other classifiers as well (e.g. gradient boosting decision trees and general Pytorch neural networks (Demetrio et al., 2021, 2020) For this example, we choose to test the following strategies.

**Partial DOS.** This attack leverage the editing of a fraction of the unused DOS header, kept inside compiled binaries for retro-compatibility (Demetrio et al., 2019).

**Extend.** This attack leverage the extension of the unused DOS header, by shifting the real one by a custom amount, and injecting adversarial content there (Demetrio et al., 2021). This is achieved by exploiting the presence of an offset inside the DOS header that instructs the loader where to look for the content of the program. Then, injected content must be compliant with the constraints imposed by the file format.

**Shift.** This attack inject new content before the first section, by shifting all the content by the custom amount (Demetrio et al., 2021). This manipulation exploits the offsets inside the header of the program that instructs the loader where the sections start inside the binary. Since all sections must be aligned to a multiple of the file alignment, the content must match this constraint in order to not break the structure.

**Padding.** This attack leverages the appending of new bytes at the end of the executable (Kolosnjaji et al., 2018). Such content is not controlled by the loader, since there are no pointers to such addition inside neither the code and the header.

**GAMMA-padding.** This attack leverage the padding manipulation to inject content extracted from benign software (Demetrio et al., 2020), whose size is controlled by a regularization parameter to avoid uncontrolled growth of the manipulation size.

### 3.1 Experimental results

We test all the presented strategies in both white-box and black-box settings, aside for GAMMA-padding which is evaluated only on the latter. The results are shown in Table 2.

**White-box attacks.** We set the maximum number of iterations to 50, and we observe how the detection rate decreases while optimizing the injected content. Our library is able to identify a weakness to attacks that perturb the header of programs; in particular, the Extend attack is able to decrease the detection rate close to 0 in only few iterations.

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2. https://anaconda.org
3. https://www.docker.com
Table 2: Detection Rates (DRs) of MalConv against white-box/black-box attacks, optimized with an increasing number of iterations/queries.

**Black-box attacks.** We bound the maximum number of queries to 500 for the black-box attacks. For *GAMMA-padding*, we extracted 100 .data sections from legitimate programs, and we set the regularization parameter to $10^{-5}$. Since black-box attacks do not rely on gradients, but they query the model to estimate a direction, they are less effective than their white-box counterparts. Differently, *GAMMA-padding* it optimizes directly the injection of larger chunks of benign content into the malware sample, rather than trying to optimize each single injected byte. This is enough for decreasing the detection rate close to 0.1.

## 4. Conclusions and Future Work

We present secml-malware, a tool for pentesting the robustness of machine learning Windows malware classifiers. To showcase its effectiveness, we present results against a state-of-the-art deep neural network, in both white-box and black-box settings. We remark this is the first library that contains both gradient and gradient-free techniques focused on this domain, and we have evidence that our library is being employed in research work published in top-tier venues (Quiring et al., 2020; Yuste et al., 2022; Trizna, 2022; Rigaki and Garcia, 2023; Gibert et al., 2023; Kuppa and Le-Khac, 2021; Liu et al., 2024). Currently, secml-malware has 195 stars on GitHub, 46 forks, and an average monthly quota of 500 downloads.\(^4\) We have already closed issues raised by the community, by fixing bugs and replying to curiosities from interested users.\(^5\) As future work, we plan to extend the attacks implemented in secml-malware to also target classifiers that extract information from runtime behaviour of malware. This line of work would be indeed beneficial also for the defense side, as secml-malware would become an ubiquitous tool for testing any kind of machine-learning malware classifier.

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\(^4\) https://pypistats.org/packages/secml-malware
\(^5\) https://github.com/pralab/secml_malware/issues?q=is%3Aissue+is%3Aclosed
References

Hyrum S Anderson and Phil Roth. Ember: an open dataset for training static pe malware machine learning models. *arXiv preprint arXiv:1804.04637*, 2018.

Hyrum S Anderson, Anant Kharkar, Bobby Filar, and Phil Roth. Evading machine learning malware detection. *black Hat*, 2017.

Raphael Labaca Castro, Corinna Schmitt, and Gabi Dreo. Aimed: Evolving malware with genetic programming to evade detection. In *2019 18th IEEE International Conference On Trust, Security And Privacy In Computing And Communications/13th IEEE International Conference On Big Data Science And Engineering (TrustCom/BigDataSE)*, pages 240–247. IEEE, 2019.

Scott E Coull and Christopher Gardner. Activation analysis of a byte-based deep neural network for malware classification. In *2019 IEEE Security and Privacy Workshops (SPW)*, pages 21–27. IEEE, 2019.

Luca Demetrio, Battista Biggio, Giovanni Lagorio, Fabio Roli, and Alessandro Armando. Explaining vulnerabilities of deep learning to adversarial malware binaries. *Proceedings of the Third Italian Conference on CyberSecurity (ITASEC)*, 2019.

Luca Demetrio, Battista Biggio, Giovanni Lagorio, Fabio Roli, and Alessandro Armando. Functionality-preserving black-box optimization of adversarial windows malware, 2020.

Luca Demetrio, Scott E. Coull, Battista Biggio, Giovanni Lagorio, Alessandro Armando, and Fabio Roli. Adversarial examples: A survey and experimental evaluation of practical attacks on machine learning for windows malware detection, 2021.

Félix-Antoine Fortin, François-Michel De Rainville, Marc-André Gardner, Marc Parizeau, and Christian Gagné. DEAP: Evolutionary algorithms made easy. *Journal of Machine Learning Research*, 13:2171–2175, jul 2012.

Daniel Gibert, Giulio Zizzo, and Quan Le. Certified robustness of static deep learning-based malware detectors against patch and append attacks. In *Proceedings of the 16th ACM Workshop on Artificial Intelligence and Security*, pages 173–184, 2023.

Bojan Kolosnjaji, Ambra Demontis, Battista Biggio, Davide Maiorca, Giorgio Giacinto, Claudia Eckert, and Fabio Roli. Adversarial malware binaries: Evading deep learning for malware detection in executables. In *2018 26th European Signal Processing Conference (EUSIPCO)*, pages 533–537. IEEE, 2018.

Felix Kreuk, Assi Barak, Shir Aviv-Reuven, Moran Baruch, Benny Pinkas, and Joseph Keshet. Deceiving end-to-end deep learning malware detectors using adversarial examples. *arXiv preprint arXiv:1802.04528*, 2018.

Aditya Kuppa and Nhien-An Le-Khac. Adversarial xai methods in cybersecurity. *IEEE transactions on information forensics and security*, 16:4924–4938, 2021.
Liang Liu, Xinyu Kuang, Lin Liu, and Lei Zhang. Defend against adversarial attacks in malware detection through attack space management. *Computers & Security*, 141:103841, 2024.

Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, et al. Pytorch: An imperative style, high-performance deep learning library. *Advances in Neural Information Processing Systems*, 32:8026–8037, 2019.

Maura Pintor, Luca Demetrio, Angelo Sotgiu, Marco Melis, Ambra Demontis, and Battista Biggio. secml: Secure and explainable machine learning in python. *SoftwareX*, 18:101095, 2022.

Erwin Quiring, Lukas Pirch, Michael Reimsbach, Daniel Arp, and Konrad Rieck. Against all odds: Winning the defense challenge in an evasion competition with diversification. *arXiv preprint arXiv:2010.09569*, 2020.

Edward Raff, Jon Barker, Jared Sylvester, Robert Brandon, Bryan Catanzaro, and Charles K Nicholas. Malware detection by eating a whole exe. In *Workshops at the Thirty-Second AAAI Conference on Artificial Intelligence*, 2018.

Maria Rigaki and Sebastian Garcia. Stealing and evading malware classifiers and antivirus at low false positive conditions. *Computers & Security*, 129:103192, 2023.

Joshua Saxe and Konstantin Berlin. Deep neural network based malware detection using two dimensional binary program features. In *Malicious and Unwanted Software (MALWARE), 2015 10th International Conference on*, pages 11–20. IEEE, 2015.

Mahmood Sharif, Keane Lucas, Lujo Bauer, Michael K Reiter, and Saurabh Shintre. Optimization-guided binary diversification to mislead neural networks for malware detection. *arXiv preprint arXiv:1912.09064*, 2019.

Octavian Suciu, Scott E Coull, and Jeffrey Johns. Exploring adversarial examples in malware detection. In *2019 IEEE Security and Privacy Workshops (SPW)*, pages 8–14. IEEE, 2019.

Dmitrijs Trizna. Quo vadis: hybrid machine learning meta-model based on contextual and behavioral malware representations. In *Proceedings of the 15th ACM Workshop on Artificial Intelligence and Security*, pages 127–136, 2022.

Javier Yuste, Eduardo G Pardo, and Juan Tapiador. Optimization of code caves in malware binaries to evade machine learning detectors. *Computers & Security*, 116:102643, 2022.