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PE Parser: A Python package for Portable Executable files processing

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ABSTRACT

PE Parser is a Python package to parse and work with the hexadecimal representation of executables' binary content and its assembly language source code. *PE Parser* has been designed to provide a class-based and user-friendly interface for the extraction of well-known features commonly used for the task of malware detection and classification such as byte and opcode N-Grams, API function calls, the frequency of use of the registers, characteristics of the Portable Executable file sections, among others. In addition, *PE Parser* has various command line tools to visualize the executables as grayscale images or as a stream of entropy values.

Code metadata

Current code version	v1.0.0
Permanent link to code/repository used for this code version	https://github.com/SoftwareImpacts/SIMPAC-2022-131
Permanent link to Reproducible Capsule	https://codeocean.com/capsule/9987564/tree/v1
Legal Code License	MIT License
Code versioning system used	git
Software code languages, tools, and services used	Python, NLTK
Compilation requirements, operating environments & dependencies	Python>= 3.6.9
If available Link to developer documentation/manual	https://pe-parser.readthedocs.io/en/latest/
Support email for questions	daniel.gibertlla@gmail.com

1. Introduction

Feature engineering is a key component of any machine learning system's pipeline. Broadly speaking, feature engineering refers to the process of transforming raw data into meaningful features used to feed the desired learning algorithm. For the task of malware detection and classification, it is common to extract features from both the binary content of a Portable Executable (PE) file and its corresponding assembly language source code. Common features are byte and opcode N-gram features, entropy statistics, the frequency of use of the registers, the invocation or not of Application Programming Interface (API) functions and system calls, etcetera. Afterwards, the resulting features are used to train a machine learning model [1–4].

PE Parser is a Python package for the preprocessing, the extraction of features and the visualization of Portable Executable files, both as grayscale images [5,6] and as a stream of entropy values [7,8]. Existing Python libraries, such as EMBER [9] and PE Miner [10], extract features and characteristics from the Portable Executable files headers, i.e MS-DOS Header, COFF file header, and the Optional header. Additionally, *PE Parser* complements the aforementioned libraries by providing various procedures to extract well-known features from the assembly language source code of PE files. *PE Parser* has been designed to provide a class-based and user-friendly interface to facilitate the extraction of well-known features [1,2] from Portable Executables files that are commonly used to build malware detection systems powered by machine learning. Furthermore, *PE Parser* provides various command line tools to visualize the executables as grayscale images [5,6,11] or as a stream of entropy values (structural entropy) [7,8].

2. Key features

PE Parser can be used to extract features from Portable Executable files in one of the following two formats:

- Hexadecimal representation of its binary content. Cf. Fig. 1(a). This representation represents the machine code as a sequence of hexadecimal values. The first value indicates the starting address

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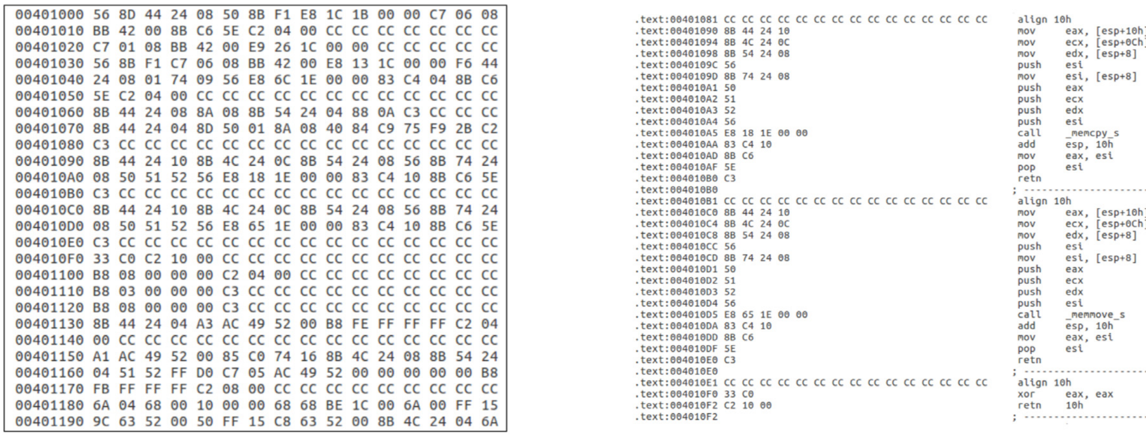

(a) Hexadecimal view.

(b) Assembly view.

Fig. 1. Hexadecimal and assembly view of PE executables [13].

of the machine codes in the memory, and each hexadecimal value (byte) carries meaningful information of the Portable Executable file such as instruction codes and data. There are various tools to obtain the hexadecimal view of a binary file such as PE Explorer,[1] HxD,[2] among others.

- Assembly language source code. Cf. Fig. 1(b). The assembly language source code contains the symbolic machine code of the executable as well as metadata information such as rudimentary function calls, memory allocation and variable information. There are various tools for disassembling Portable Executable files such as IDA Pro,[3] Radare2,[4] Ghidra,[5] etcetera.

These file formats are the ones commonly used during static analysis to extract features from executables without actually running the program. For more information about both file formats we refer the readers to the Microsoft Malware Classification Challenge dataset [12], a high-quality public labeled benchmark available for malware classification research. This dataset has become the standard benchmark to evaluate machine learning approaches for malware classification and currently, it is publicly available in the Kaggle platform.[6]

Currently, *PE Parser* contains code to extract the following features:

- Hexadecimal-based features. Features extracted from the hexadecimal representation of executable's binary content.
  - Byte N-gram features.
  - Entropy-based features.
  - Haralick features from the grayscale image representation of the hexadecimal view of executables.
  - Local Binary Pattern features from the grayscale image representation of the hexadecimal view of executables.
- Assembly-based features.
  - Opcode N-gram features.
  - Register features.
  - Data define directive features.
  - Section characteristics features.
  - Symbol frequency features.
  - Application Programming Interface (API) function calls features.
  - Pixel intensity features extracted from the grayscale representation of the assembly code.
  - Miscellaneous features (Keywords).

A complete description of the aforementioned features is provided in the works of Ahmadi et al. [1], Zhang et al. [2], and Gibert et al. [4].

3. Visualization tools

PE Parser provides various command-line tools to visualize the executables as follows:

Grayscale image representation. Nataraj et al. [5] proposed to visualize and classify malware (in PE format) using image processing techniques. Cf. Fig. 2. In their work, binary executables are visualized as grayscale images, where every byte is reinterpreted as one pixel in the image. Then, the resulting array is reorganized as a 2-D array and can be visualized as an image, with values ranging from 0 to 255.

This grayscale image representation can be used to classify malware as images of malware belonging to the same family are similar between them while distinct from those belonging to other families as demonstrated in the work of Gibert et al. [6] and others [14].

Structural entropy representation. Portable Executable files can be visualized as a stream of entropy values, or structural entropy [7,8]. To calculate the structural entropy representation of an executable, you need to split the executable into chunks of fixed size, i.e. 1024 bytes, and calculate the amount of entropy for each chunk. Cf. Fig. 3.

4. Impact

PE Parser is intended for scientists and researchers who would like to conduct research on malware detection. *PE Parser* has been designed to be used by both computer security researchers and by students in courses on malware analysis, machine learning and computer security. Currently, it has been already used in a number of scientific publications [3,6,8,13,15–17]. Besides, the authors are aware of numerous security practitioners that have used one or more of the features implemented by PE Parser to build their malware detection systems [1,2]. In

[1] http://www.heaventools.com/flexhex-hex-editor.htm
[2] https://mh-nexus.de/en/hxd/
[3] https://www.hex-rays.com/products/ida/
[4] https://rada.re/n/
[5] https://ghidra-sre.org/
[6] https://www.kaggle.com/c/malware-classification

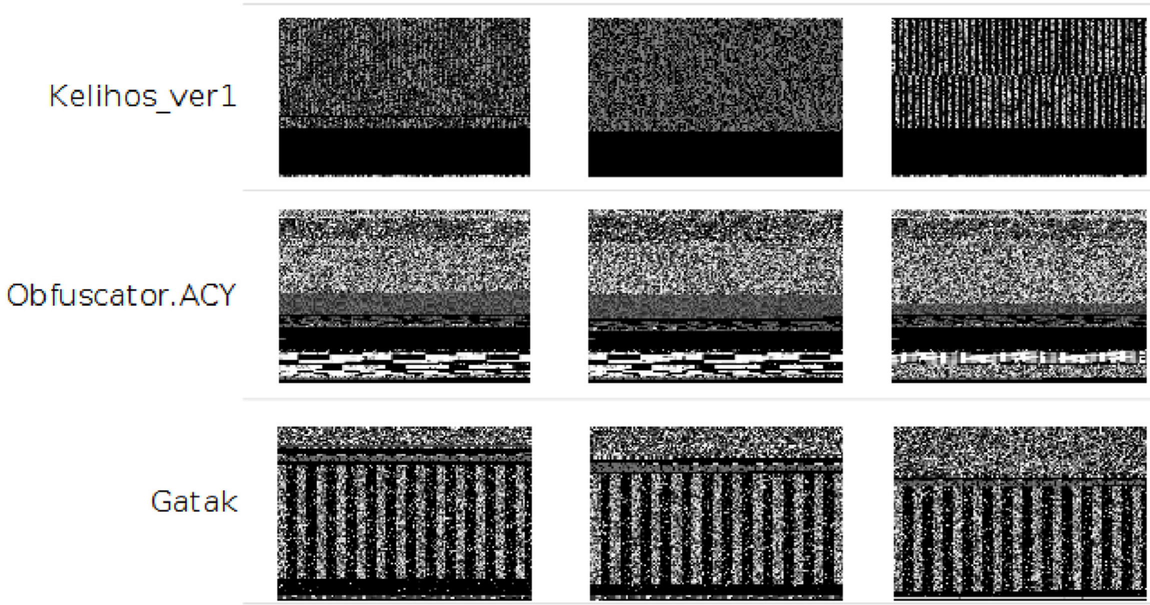

Fig. 2. Grayscale image representation of samples belonging to the Kelihos_ver1, Obfuscator.ACY and Gatak families [6].

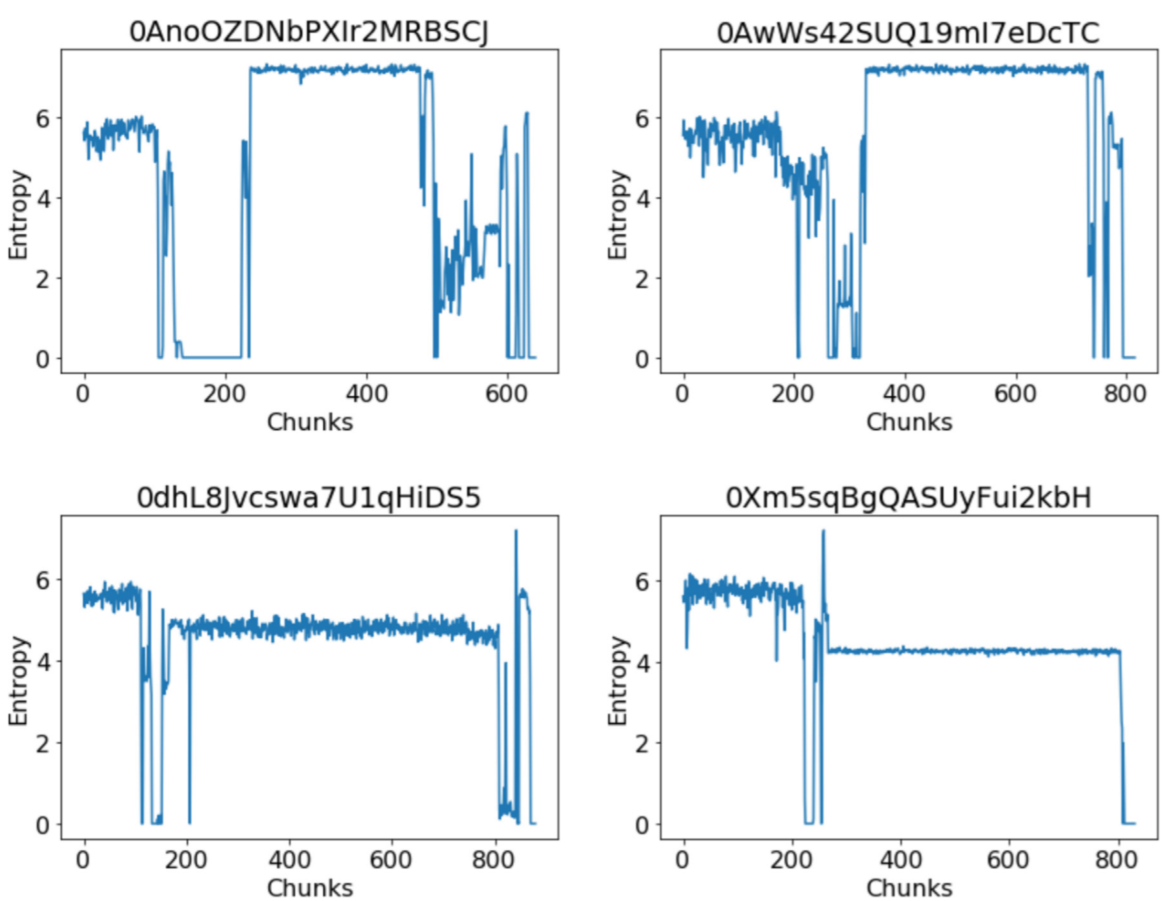

Fig. 3. Structural entropy representation of samples belonging to the Ramnit and Gatak families [8].

addition, the representation of malware's binary content as a grayscale image has been used in at least the following papers [5,6,18–27] while the structural entropy representation of malware has been used in at least next papers [7,8,28–36]. Furthermore, *PE Parser* can be used to train deep learning models [3,15,37–41] by using as input the hexadecimal byte values and the opcodes extracted from the hexadecimal representation of malware's binary content and its assembly language source code, respectively.

5. Future work

In the future we intend to extend the library with additional types of features and visualization tools such as entropy graphs [36] and function call graphs [42]. On the one hand, entropy graphs can be created using a two steps process. First, binary files are converted to bitmap images. Second, the entropy value of each line of the bitmap images is calculated. On the other hand, the function call graph is a control-flow graph that represents calling relationships between functions/subroutines in a computer program.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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