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NEW APPROACH FOR NETWORK ATTACK DETECTION BASED ON IMAGE RECOGNITION

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How does this start?

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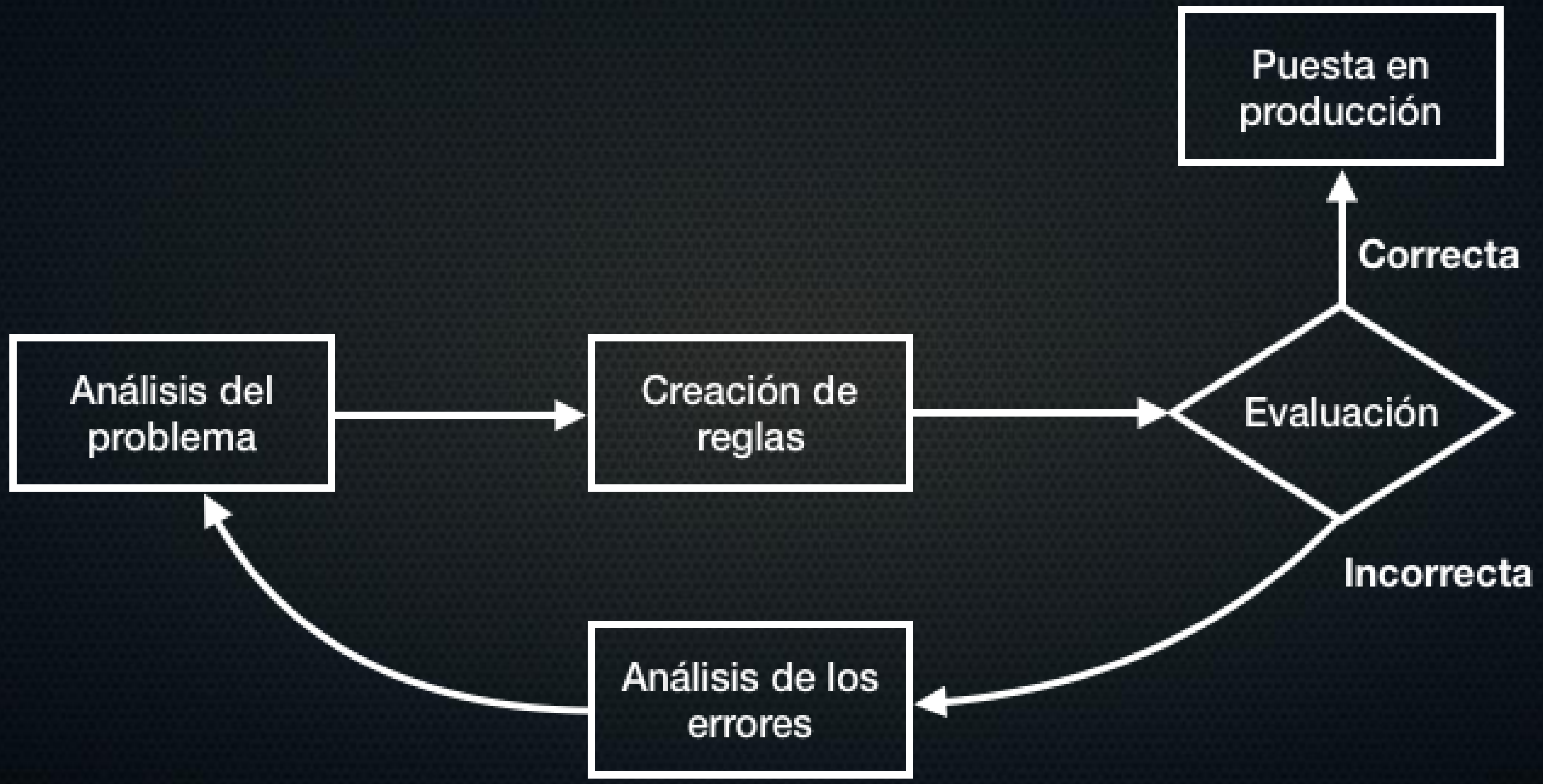
Intrusion Detection

Intrusion Detection is categorized into two types [1]:

- **Rule-based and heuristic approaches:** Produces few false positives. Detects known attacks. Does not work well for detecting new attacks.
- **Anomaly-based approaches:** Profiles normal system behavior. Can detect new attacks. Generates more false positives.

[1] Lee, W., and Stolfo, S. J. Data mining approaches for intru- sion detection. In Proc. of the 7th USENIX Security Symposium (USA, 1998), vol. 7, USENIX Association, pp. 79–94.

Rule-based and heuristic approaches



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Anomaly Detection

- An anomaly is an event that deviates from normal or expected behavior and is suspicious, in this case, from a security perspective.
- Anomaly detection is the identification of rare elements, events, or observations that raise suspicions by significantly differing from most of the data [1].
- Anomaly detection was proposed for intrusion detection systems (IDS) by Dorothy Denning in 1986 [2].
- Anomalies can occur due to two main factors [3]:

  Performance-related

  Security-related

[1] https://en.wikipedia.org/wiki/Anomaly_detection
[2] D. E. Denning, P. G. Neumann, Requirements and model for IDES—A real-time intrusion detection system, 1985.
[3] Thottan, M., and Ji, C. Anomaly detection in IP networks. IEEE Transactions on Signal Processing 51, 8 (August 2003), 2191–2204.

Artificial Intelligence and Cybersecurity

“Today’s AI has important applications in cybersecurity, and is expected to play an increasing role for both defensive and offensive cyber measures.” [1]

[1] https://obamawhitehouse.archives.gov/sites/default/files/whitehouse_files/microsites/ostp/NSTC/preparing_for_the_future _of_ai.pdf

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AI Algorithms Classification

- Supervised learning.
- Semi-supervised learning.
- Unsupervised learning.
- Reinforcement learning.

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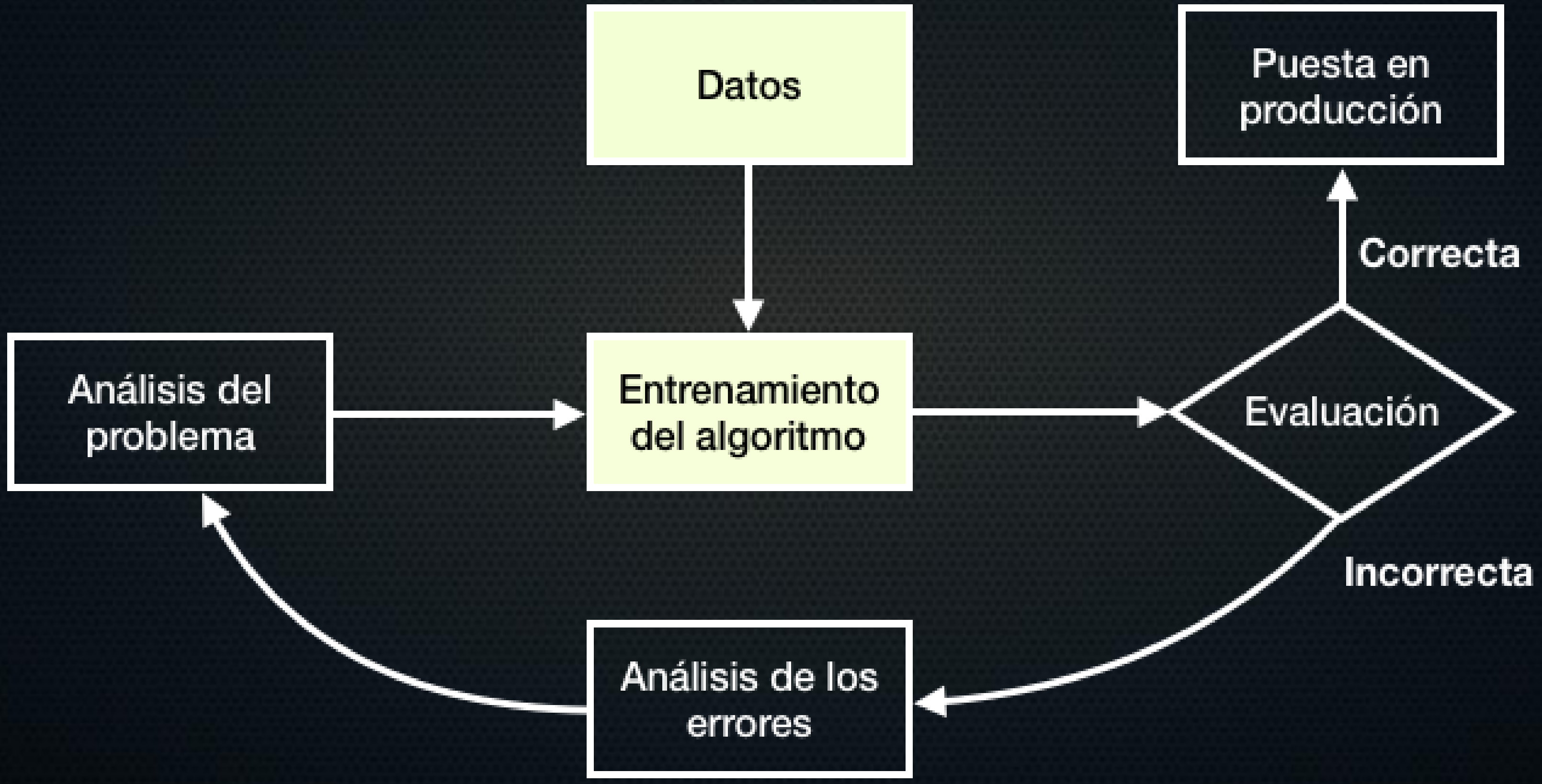
Based on Machine Learning



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Problems in the application of Machine Learning techniques

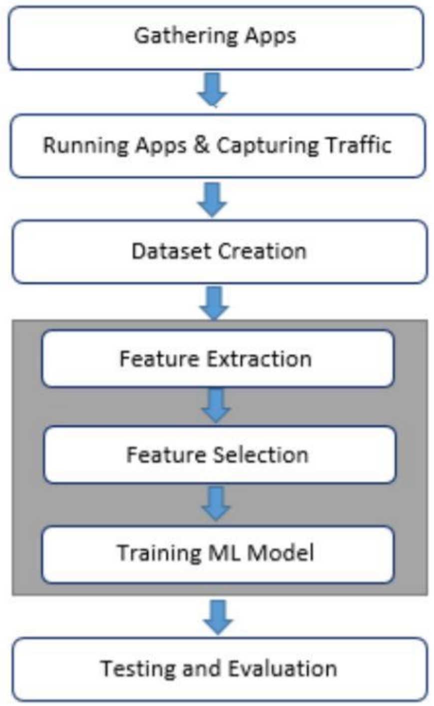

Figure 1: Procedure of Proposed Model

Towards a Network-Based Framework for Android Malware Detection and Characterization

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Problems in the application of Machine Learning techniques

Out[4]:

	duration	protocol_type	service	flag	src_bytes	dst_bytes	land	wrong_fragment	urgent	hot	...	dst_host_count	dst_host_srv_count	dst_host_same_
95141	0	tcp	http	SF	214	14939	0	0	0	0	...	52	255	
37486	0	tcp	private	S0	0	0	0	0	0	0	...	255	2	
34926	0	tcp	http	REJ	0	0	0	0	0	0	...	255	8	
34589	0	tcp	http	SF	257	259	0	0	0	0	...	255	255	
11420	0	udp	other	SF	516	4	0	0	0	0	...	255	255	
46955	0	tcp	private	S0	0	0	0	0	0	0	...	255	20	
32661	0	tcp	smtp	RSTO	0	0	0	0	0	0	...	255	1	
21066	0	icmp	eco_i	SF	8	0	0	0	0	0	...	2	129	
22128	0	tcp	private	S0	0	0	0	0	0	0	...	255	17	
21455	0	udp	private	SF	1	0	0	0	0	0	...	255	110	

M. Tavallaee, E. Bagheri, W. Lu, and A. Ghorbani, "A Detailed Analysis of the KDD CUP 99 Data Set," Submitted to Second IEEE Symposium on Computational Intelligence for Security and Defense Applications (CISDA), 2009.

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END-TO-END LEARNING

We delegate the feature extraction function to the algorithm: **Deep Learning**

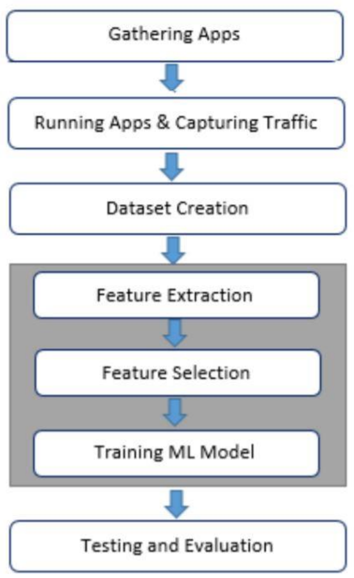
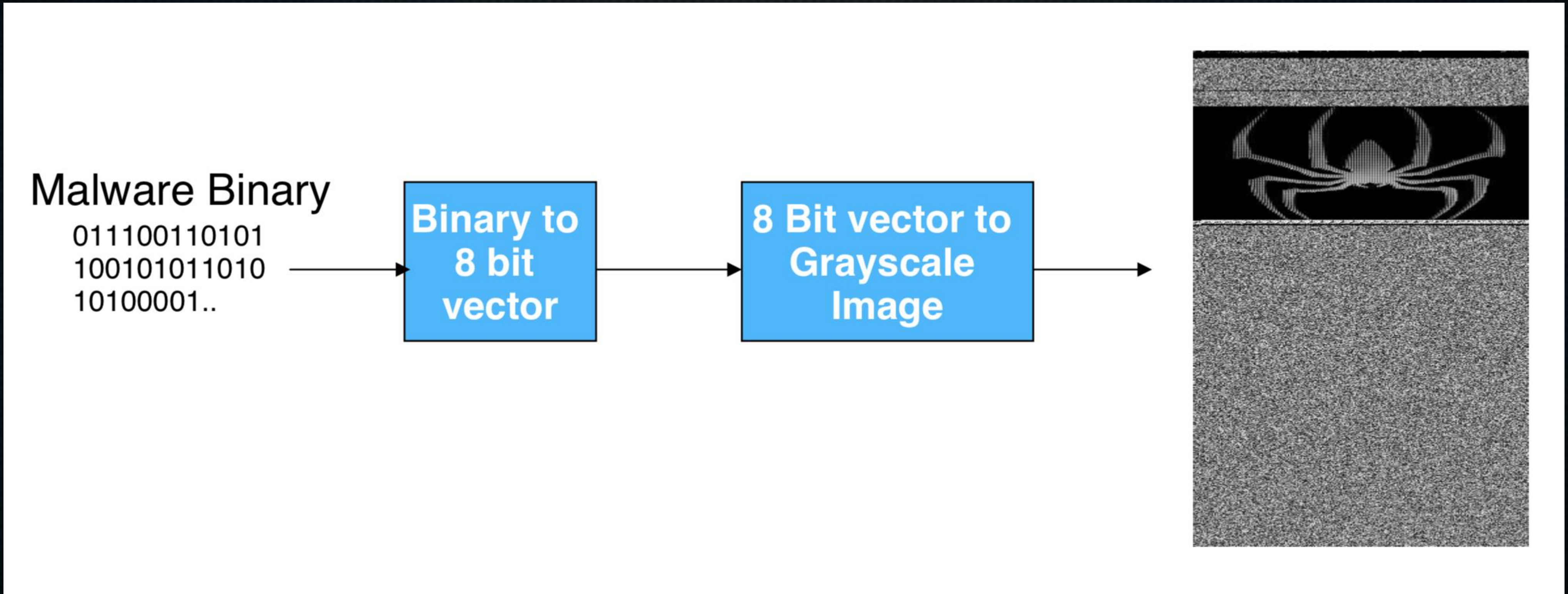


Figure 1: Procedure of Proposed Model

Malware Images: Visualization and Automatic Classification



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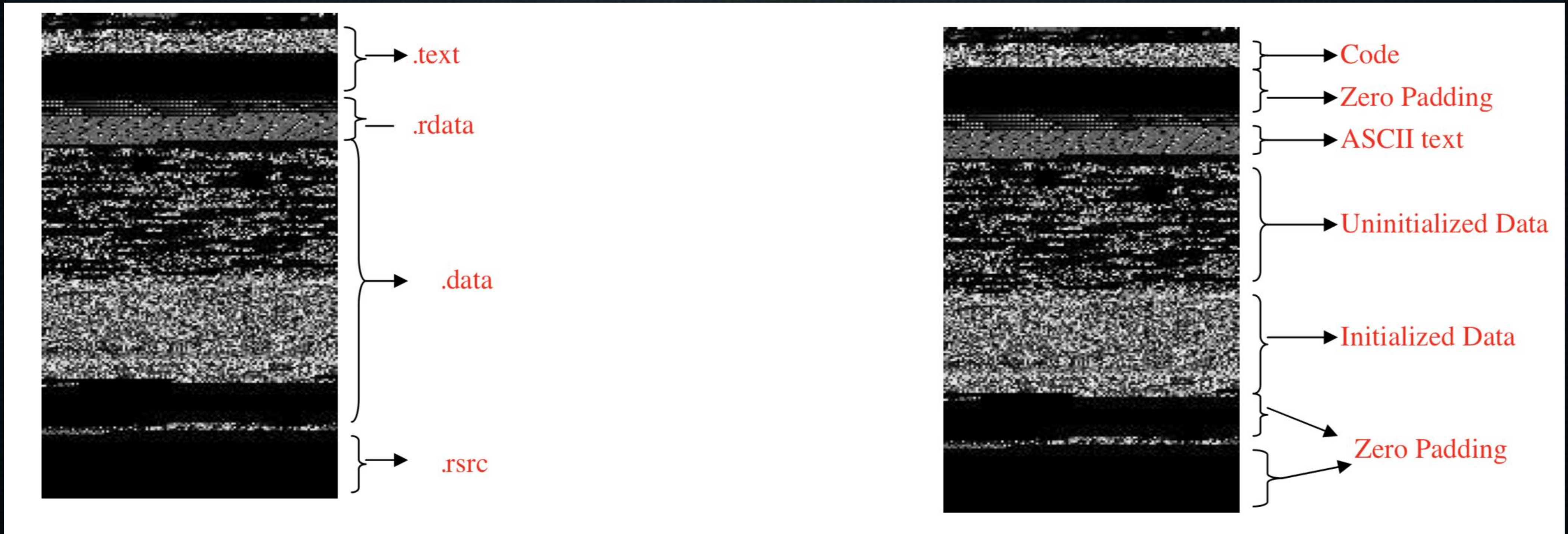
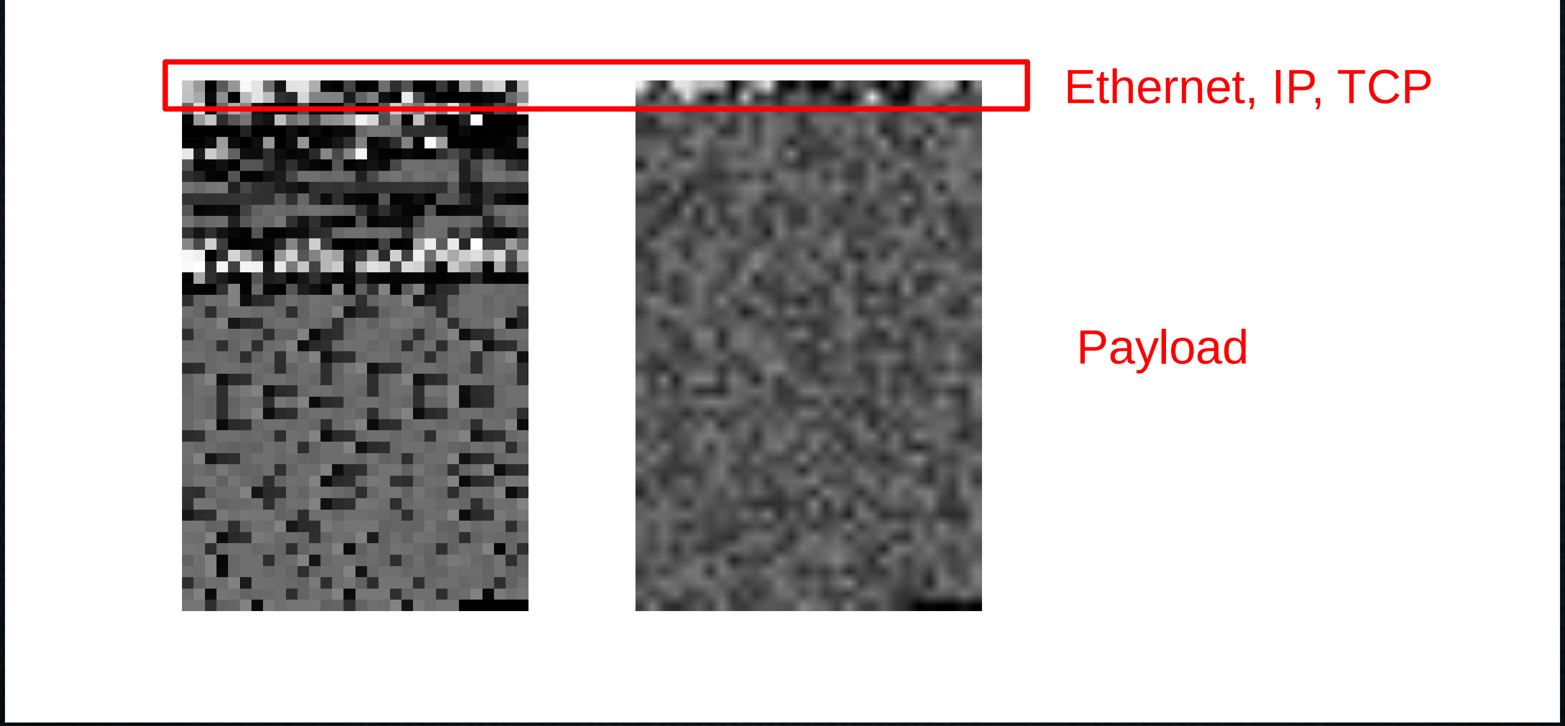
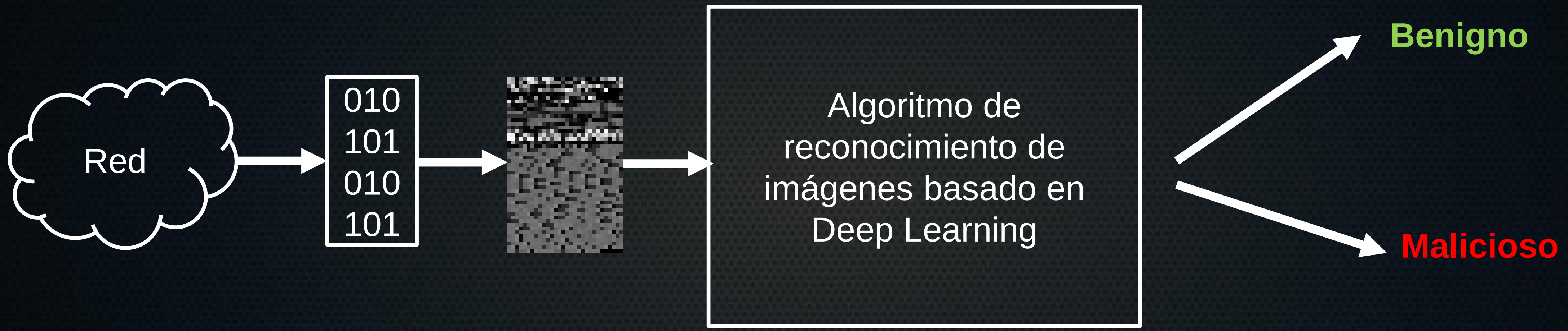
Malware Images: Visualization and Automatic Classification



Malware Images: Visualization and Automatic Classification




Red
010
101
010
101
Algoritmo de reconocimiento de imágenes basado en Deep Learning
Benigno
Malicioso

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Where do we start?

Where do we start?

1. Convert network traffic into images.
2. Select and train a Deep Learning algorithm.
3. Offline evaluation.
4. Save the model.
5. Deploy the model in real-time.
6. Online evaluation.

Convert network traffic into images

01005e000001f88e85ded79208004600002000004000
0102432dc0a80101e000000194040000110aeef50000
0000803f5d5c071b8c8590bb3db9080045000047b43b
0000ff1183cac0a8012cc0a80123db3c003500336bf6bd
5701000001000000000000c70726f6473746f7261676
53208636c6f756461707070036e657400000100010 1005
e7ffffab853ac6d1ce20800450000099522a00000111b56
0c0a80127effffffad23c076c008545e84d2d5345415243
48202a20485454502f312e310d0a484f53543a2032333
92e3235352e3235352e323

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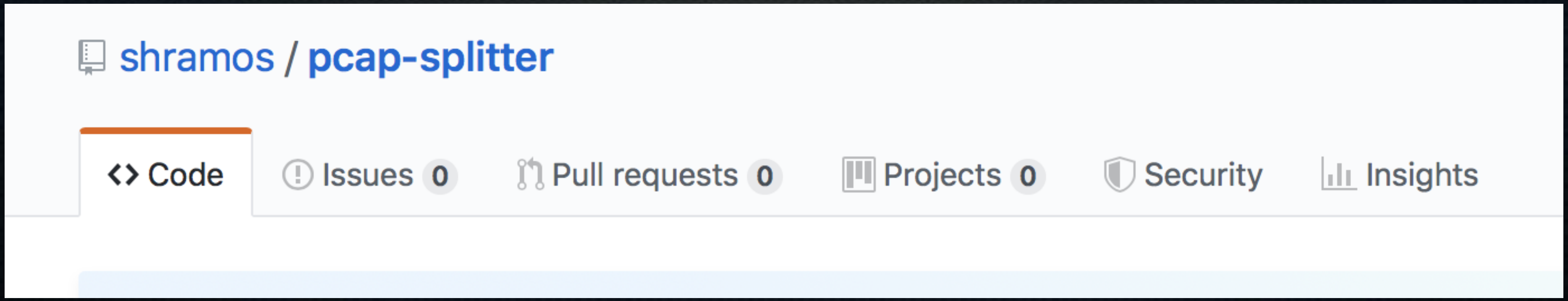
Convert network traffic into images

Divide by packets, sessions, connections, flows, size, number of packets, etc.



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Train a Deep Learning algorithm

IMAGENET Large Scale Visual Recognition Challenge (ILSVRC)

ImageNet Classification with Deep Convolutional Neural Networks

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Geoffrey E. Hinton
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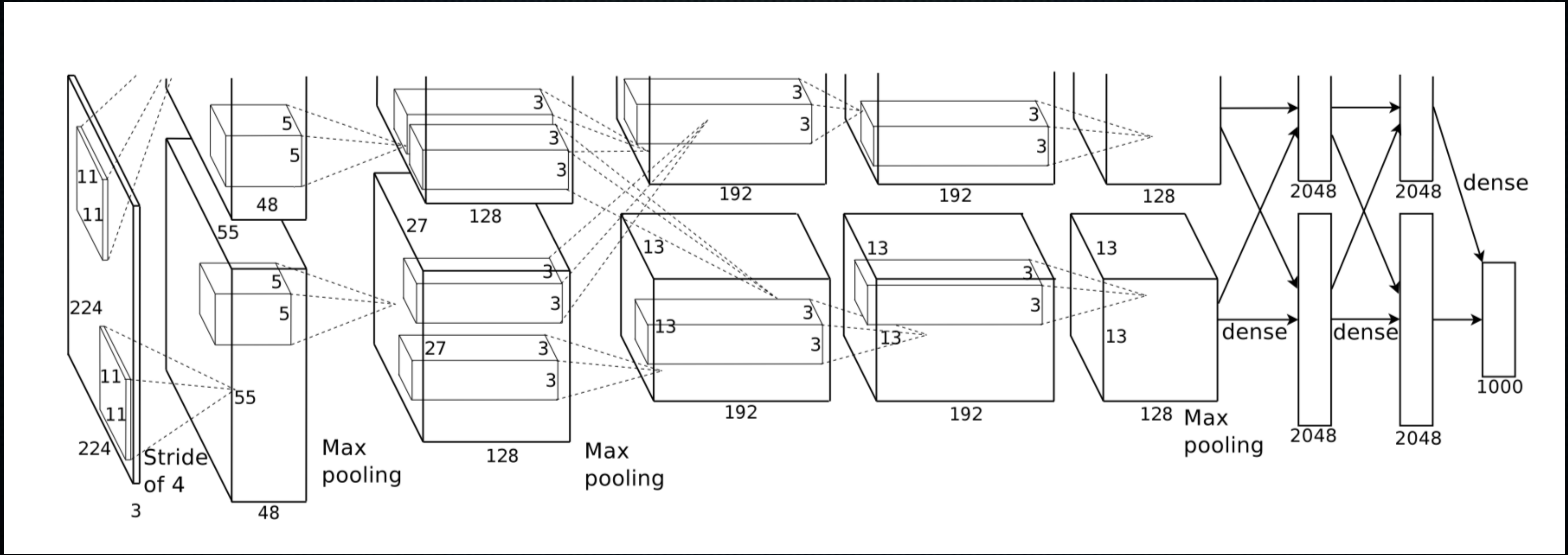
Train a Deep Learning algorithm



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Offline evaluation

CICIDS2017: *Iman Sharafaldin, Arash Habibi Lashkari, and Ali A. Ghorbani, "Toward Generating a New Intrusion Detection Dataset and Intrusion Traffic Characterization", 4th International Conference on Information Systems Security and Privacy (ICISSP), Portugal, January 2018*

CICInvesAndMal2019: *Laya Taheri, Andi Fitriah Abdulkadir, Arash Habibi Lashkari; Extensible Android Malware Detection and Family Classification Using Network-Flows and API-Calls, The IEEE (53rd) International Carnahan Conference on Security Technology, India, 2019*

CSE-CIC-IDS2018: *Iman Sharafaldin, Arash Habibi Lashkari, and Ali A. Ghorbani, "Toward Generating a New Intrusion Detection Dataset and Intrusion Traffic Characterization", 4th International Conference on Information Systems Security and Privacy (ICISSP), Portugal, January 2018*

A total of more than 100GB of network traffic

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Offline evaluation

Algorithm	Pr	Rc	F1	Execution (Sec.)
KNN	0.96	0.96	0.96	1908.23
RF	0.98	0.97	0.97	74.39
ID3	0.98	0.98	0.98	235.02
Adaboost	0.77	0.84	0.77	1126.24
MLP	0.77	0.83	0.76	575.73
Naive-Bayes	0.88	0.04	0.04	14.77
QDA	0.97	0.88	0.92	18.79

Dataset:	**Training (10-fold cross validation)**								
Scenario:	**A (Malware Binary)**			**B (Malware Category)**			**C (Malware Families)**		
Algorithm:	RF	KNN	DT	RF	KNN	DT	RF	KNN	DT
Precision (%):	84.00	83.60	85.10	46.50	45.70	46.50	22	21.50	21.00
Recall (%):	87.50	87.30	88.00	45.50	44.80	44.70	21.50	21.60	21.40

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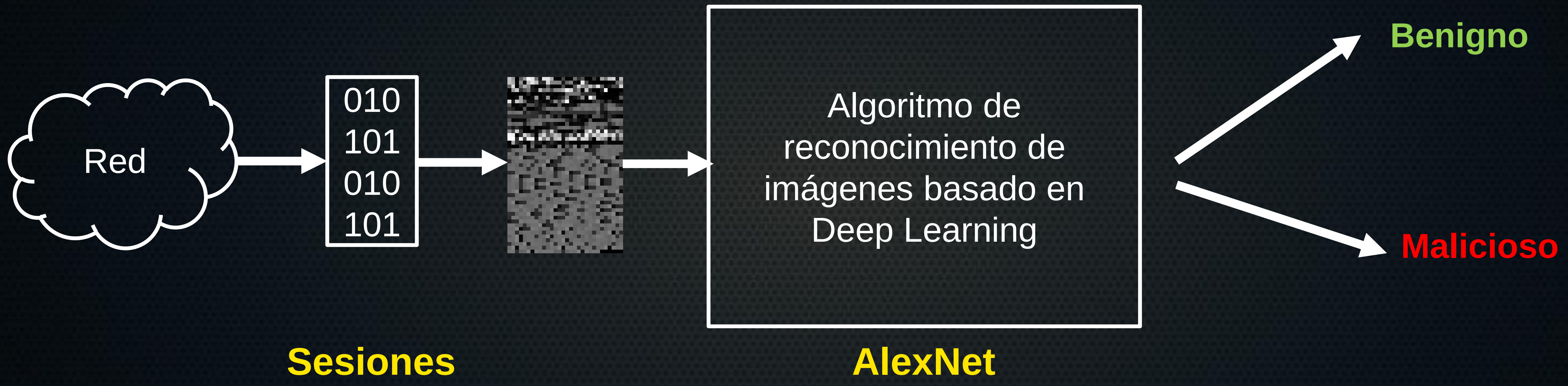
Deployment of the model in real-time



Offline evaluation - DEMO

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Advantages

- Does not require feature extraction or selection.
- Increases efficiency and enables real-time detection.
- Allows the creation of customized models for specific environments.
- Does not require an analyst's expertise for creating and maintaining detection rules.

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Disadvantages

It requires a large dataset to function correctly. While benign traffic is easy to obtain, malicious traffic is not.

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THANK YOU VERY MUCH!

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