#### MaskDroid: Robust Android Malware Detection with Masked Graph Representations

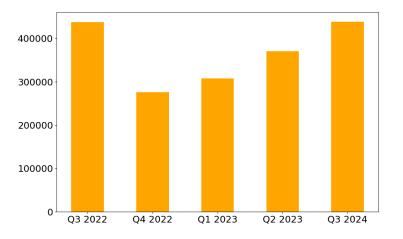
Jingnan Zheng<sup>\*</sup>, Jiahao Liu<sup>\*</sup>, An Zhang, Jun Zeng, Ziqi Yang, Zhenkai Liang, Tat-Seng Chua

IEEE/ACM ASE, Oct. 2024



## Security Threats and Risks of Android Malware

#### Android malware poses increasing security threats and risks



Number of detected malicious install packages

# Image: Status and Status

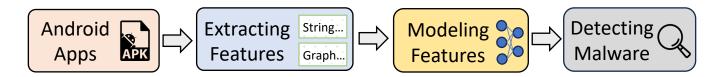
targeted over 600 global brands.

Discovered by Zimperium's zLabs team, this malware has been found in over 105,000 samples.

## Detecting Android malware before installation is the key to mitigate these security threats and risks

## **ML-based Android Malware Detection**

Characterize apps and identify malicious patterns to distinguish malware



General workflow of ML-based Android malware detection

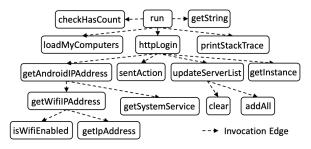
Syntax-based methods [Drebin @NDSS'14, XMAL @TOSEM'21, ...]

• Model app behaviors with discrete features, e.g., permission, API calls

#### Semantic-based methods [Malscan @ASE'19, MsDroid @TDSC'22, ...]

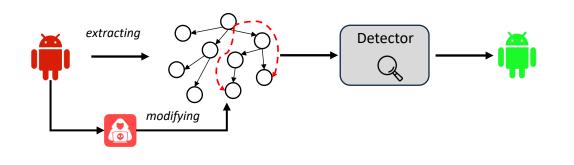
• Distill semantics from apps' graph representations





#### **Vulnerable to Adversarial Attacks**

Adversarial attack purposely modifies the graph structure to bypass the detection



A Comprehensive Study of Learning-based Android Malware Detectors under Challenging Environments

Black-box Adversarial Example Attack towards FCG Based Android Malware Detection under Incomplete Feature Information

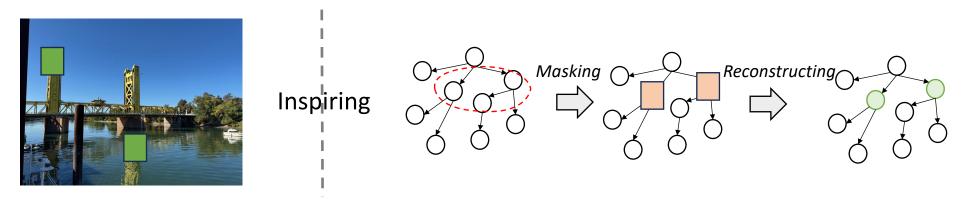
Heng Li<sup>†</sup>, Zhang Cheng<sup>‡,†</sup>, Bang Wu<sup>†</sup>, Liheng Yuan<sup>†</sup>, Cuiying Gao<sup>†</sup>, Wei Yuan<sup>†</sup>\*, Xiapu Luo\* <sup>†</sup> Huazhong University of Science and Technology <sup>\*</sup> The Hong Kong Polytechnic University <sup>‡</sup> NSFOCUS Technologies Group Co., Ltd. {liheng,wubangm,ylh,gaocy,yuanwei]@hust.edu.cn chengzhang@nsfocus.com.csxluo@comp.polyu.edu.hk

**Research Problem**: Given the graph representation, could we design a robust and effective Android malware detector?

## **Our Insights**

Masking and reconstructing mechanisms are effective for robust learning

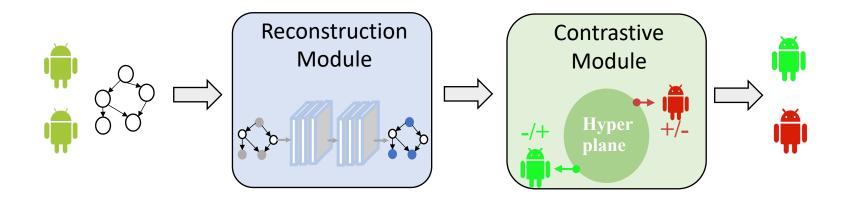
 Encourage models to capture overall information even if some features are purposely changed



Contrastive strategy can better investigate the relationships among samples

 samples within the same class are drawn closer together, while those from different classes are pushed further apart

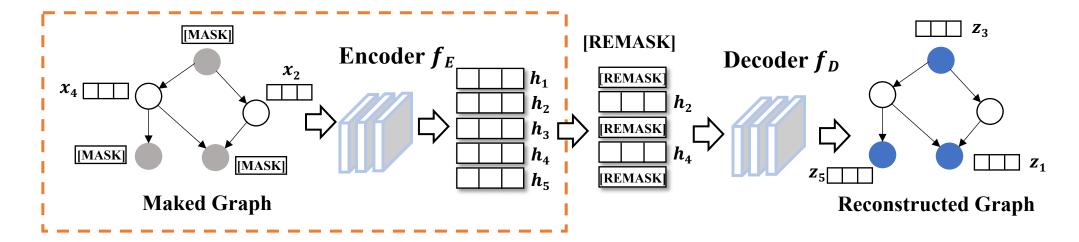
#### MaskDroid: Overview



Given an Android app, output the probability of being malicious

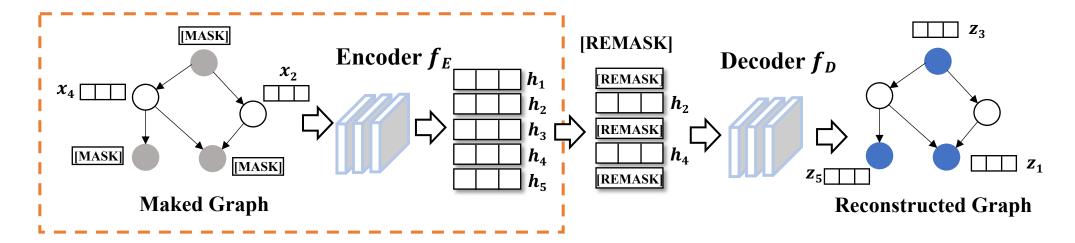
- Mask and reconstruct graphs to learn robust representations
- Separate malware with a contrastive strategy

Key Idea: masking and reconstructing the graph structure to learn a robust representation of malicious behavior



- Mask the graph to construct incomplete graph representation
  - Concatenate opcode and permission to represent graph node features
  - Apply uniform random sampling to choose a subset of nodes and mask their representations

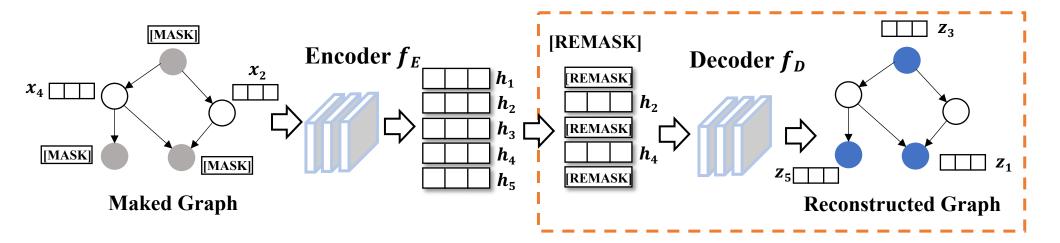
Key Idea: masking and reconstructing the graph structure to learn a robust representation of malicious behavior



- Encode the graph representation with GNN Encoder
  - Propagate and aggregate node information across edges, enabling the model capture both local and global graph dependencies
  - getAndroidAddress -> getWifilpAddress -> isWifiEnabled | getIpAddress

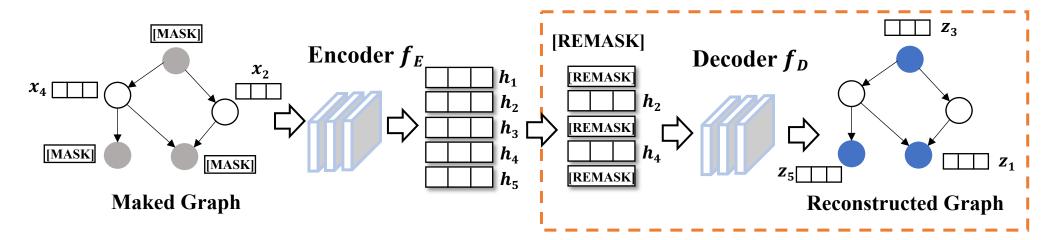


Key Idea: masking and reconstructing the graph structure to learn a robust representation of malicious behavior



- **Reconstruct** the masked nodes to allow the model can infer overall information from partial nodes and edges
  - Ensure the model recover masked nodes based solely on their surrounding nodes -> remask
  - Another GNN to capture structural information and recover nodes

Key Idea: masking and reconstructing the graph structure to learn a robust representation of malicious behavior

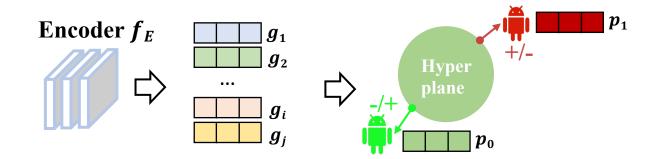


• **Objective:** measure the distance between the original node features and the reconstruction features Reconstruction Loss (*z*<sub>i</sub>,*x*<sub>i</sub>)

With the reconstruction module, MaskDroid can recover the overall graph information, even if the graph is partly corrupted

#### **Contrastive Module**

Key Idea: Apps within the same class should be closer to each other, while apps from different classes should be more distant



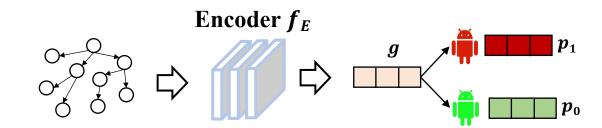
• **Define** two proxies for benign and malicious classes to guide the contrastive learning

• Each instance is pulled closer to the proxy of its own class while being pushed further from the other proxy Proxy-Based Contrastive Loss (g<sub>i</sub>, p<sub>0</sub>, p<sub>1</sub>, y<sub>i</sub>)

With the contrastive module, MaskDroid can learn a compact representation for each class and forms clear boundaries between different classes

#### **Detecting Android Malware**

Transforms the input graph into a graph-level representation using the encoder and calculate the distance with benign and malicious proxies



Detecting Android malware by calculating the distance

## **Evaluation**

#### **Experiment Setup:**

- Around 114k apps collected from AndroZoo a continuously expanding repository of Android apps sourced from platforms such as Google Play, Appchina, and Anzhi
  - Covering a wide range of apps (5 years)
  - Mirroring real-world malware distribution (the ratio of goodware to malware is set as 9:1)
  - Filtering out grayware with positive anti-virus alerts from VirusTotal

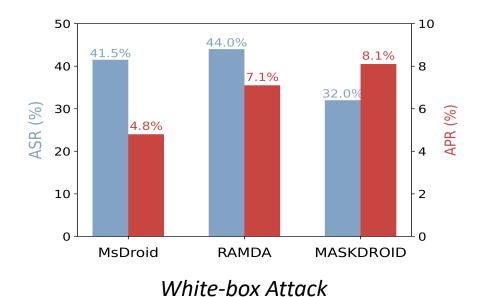
#### **Evaluation aspects:**

- Does MaskDroid improve the robustness against different adversarial attacks?
- Does MaskDroid sacrifice detection effectiveness to enhance its robustness?
- To what extent do different design choices affect MaskDroid's performance?

#### **Robustness Enhancement**

Investigate whether MaskDroid can enhance its robustness against adversarial attacks compared to existing solutions (white-box and black-box)

• Attack Success Rate (ASR), Average Perturbation Ratio (APR)



Detectors	Malscan	MamaDroid	Drebin
ASR	98.5%	69.0%	100%
APR	-	-	-
Detectors	MsDroid	RAMDA	MaskDroid
ASR	13.2%	19.2%	19.1%
AJN	13.270	13.270	13.170

black-box Attack

Compared with state-of-the-art solutions, MaskDroid enhances robustness against adversarial attack, especially in white-box attack.

## **Effectiveness Comparison**

Investigate whether the improved robustness comes at the expense of detection performance (F1-score)

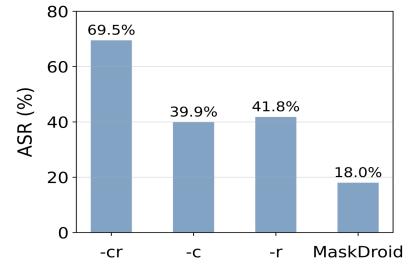
- Training and testing data within the same period
- Temporal split: Training with previous, testing with later data

Time Span	Malscan	Mamadroid	Drebin	MsDroid	RAMDA	MaskDroid
Same time	0.808	0.838	0.736	0.598	0.811	0.783
Time bias	0.473	0.421	0.573	0.317	0.546	0.582

MaskDroid achieves detection effectiveness comparable to existing Android malware detectors in both same-time and temporal bias scenarios.

## **Evaluating the Design of MaskDroid**

Investigate the effects of reconstruction and contrastive modules on the robustness and effectiveness of MaskDroid



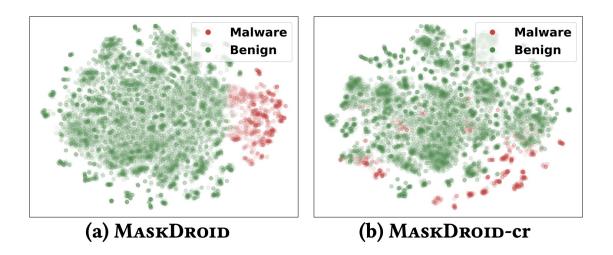
Models	Precision	Recall	F1-score	Accuracy
MaskDroid-cr	0.918	0.730	0.813	0.965
MaskDroid-c	0.886	0.688	0.774	0.958
MaskDroid-r	0.896	0.720	0.799	0.962
MaskDroid	0.772	0.883	0.824	0.961

Effectiveness of various models

Both reconstruction and contrastive modules contribute to the performance of MaskDroid.

## **Evaluating the Design of MaskDroid**

Visualize the embeddings of MaskDroid and its variant with the contrastive and reconstruction modules disabled



MaskDroid more effectively separates malware from benign apps, providing a compact representation and clear boundaries.

#### Conclusion

We propose MaskDroid:

- Learn robust graph representation encoding malicious behaviors with graph masking and reconstruction
- Incorporate proxy-based contrastive learning to better separate benign and malicious Android apps
- Release code and data at: <u>https://github.com/SophieZheng998/MaskDroid</u>