INSIGHT: Attacking Industry-Adopted Learning Resilient Logic Locking Techniques Using Explainable Graph Neural Network

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### Semiconductors in Everyday Lives



- Attacks can be launched via any abstraction layer
- Software bugs patched using updates
- What if hardware is compromised?



Protection of Hardware is essential

# **Globalized IC Supply Chain**



Note: The individual colored blocks are only a representation of the participants present in the semiconductor value chain at various points in time. They are not indicative of their relative market sizes.



#### Electronics

#### TSMC starts building 3nm plant in Taiwan worth \$20B

by Matt Hamblen I Nov 4, 2019 9:01am

### Hardware Security Threats



#### OPINION

#### The overlooked security risks of onshoring chip production

Here are four ways manufacturers can mitigate cybersecurity risks.

Published Dec. 19, 2023

Source: supplychaindive

### Hardware IP Piracy

#### Are these threats real?

US DoJ indicates prominent IC design company sufferend a loss of around 8.75 billion dollars due to IP theft



Automatic Implementation of Secure Silicon (AISS) Dr. Lok Yan

#### EDA Forms The Basis For Designing Secure Systems



How to accelerate the design process at a lower cost and with less risk.

AUGUST 3RD, 2020 - BY: ADAM CRON

source: semiengineering

A CROSS-LAYER FRAMEWORK FOR COST-EFFECTIVE INTELLECTUAL PROPERTY (IP) PROTECTION





# Logic Locking



# Logic Locking



### **Threat Model**



#### **Attacker's Resources**

- Locked design
  - Obtained by reverse-engineering the chip

#### **Attacker's Objective**

#### **Attacker's Capabilities**

Analyze reverse-engineered locked design

### Learning Resilient Logic Locking



Removes correlation between key-gate type and key-value

N. Kavand, et al., ICCAD'22; L. Alrahis, et al.; TIFS'21; N. Limaye, et al., TCAD'21; N. Limaye, et al., TCAD'22; A. B. Chowdhury, et al., DAC'23; F. Wang, et al., ISPD'23 P. Chakraborty, et al., TIFS'21; A. Alaql, et al., TVLSI'21; L. Alrahis, et al., TCAS-II'22; D. Sisejkovic et al., JETC'21; L. Alrahis, et al., DATE'22;

### Learning Resilient Logic Locking



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# **Preliminary Problem Modeling**

**GNN-based Key-Prediction** 

• Maps the problem of key-prediction to GNN-based node classification



We employ explainable ML to find the reasons behind failure of the attack

### Why Explainable ML?





#### Explainable ML provides reasons behind the prediction

**Important Features** 

**Important Nodes** 



Challenge 2: To identify reasons behind the failure of attack through explanations



*Solution 2:* We map key-prediction problem to INV/BUF prediction problem



Design	b14_C	b15_C	b17_C	b20_C	b21_C	b22_C
Solution 2	99.78	99.68	99.06	99.53	99.53	99.53

KPA improves by **1.86x** 

Semiconductor industry re-synthesizes designs upon logic locking

Challenge 3: To tackle logic re-synthesized designs

**Observation:** Explainer analysis indicates different importance scores for the gates around key-gate

Solution 3: Added attention layer to the GNN

Incorporating attention increases KPA by **10%** for re-synthesized designs



Challenge 4: To tackle insufficient training data

#### *Solution 4:* We incorporate two approaches

- Data augmentation
- Semi-supervised learning

Design	b14_C	b15_C	b17_C	b20_C	b21_C
No Data Augmentation	69.05	72.13	66.67	66.38	67.72
Solution 4	76.56	82.79	71.87	72.56	74.83
Improvement (x)	1.11 x	1.15 x	1.08 x	1.09 x	1.10 x

Data augmentation increases KPA by **1.10x** 

#### Semi-supervised learning increases KPA by **1.29x**

### Results



INSIGHT achieves KPA of **2.96x** and **1.86x** than SCOPE and OMLA

### **Results (Real-World Application)**

#### Gaussian Blurring Example



# Thank You!

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**MAXEN INCLUSION SCHOOL** 



