Data-Driven Modeling of Cyber-Physical Systems using Side-Channel Analysis

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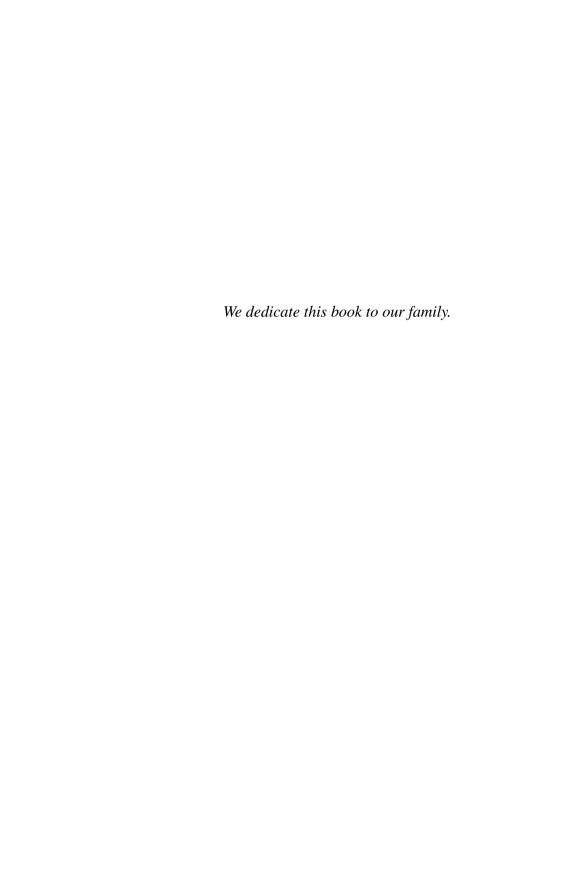
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Preface

Cyber-physical systems (CPS) consist of a unique integration of discrete cyber-domain processes and continuous physical domain components. Current modeling approaches use extensive first-principle approaches to derive the various components of CPS. However, it is difficult to model some of the stochastic phenomenon (such as environmental variation, physical process variation, etc.) of CPS using the first-principle approach. Hence, in this book we have explored a data-driven modeling approach for CPS and present various methodologies for modeling security and creating virtual replica or digital twin of the physical system. Furthermore, we will also present new algorithms to handle complex non-Euclidean data for modeling the CPS. More specifically, the book will present and exploration of the unintended emissions from the physical domain of the CPS to infer various cyber-domain states.

This book provides a new perspective on modeling the cyber-physical system using a data-driven approach. It covers the use of state-of-the-art machine learning and artificial intelligence algorithms for modeling various aspects of the CPS. It provides insight on how a data-driven modeling approach can be utilized to take advantage of the relation between the cyber and the physical domain of the CPS for aiding the first-principle approach in capturing the stochastic phenomenon affecting the CPS.

The books book provides a practical use case of the data-driven modeling approach for securing the CPS, presenting novel attack models, building and maintaining the digital twin of the physical system. Furthermore, it also provides novel data-driven algorithms to handle non-Euclidean data. In summary, this book presents a novel perspective for modeling the CPS.

The first-principle based approach for modeling the CPS is complex and timeconsuming. Below we present three major reasons for proposing a new book in this area:

Due to the advancement of machine learning and artificial intelligence algorithms, there has been a huge leap in performing data-driven modeling. However, to the best of our knowledge, there are no books covering the data-driven modeling of the CPS to aid in capturing the stochastic phenomenon affecting CPS.

viii Preface

• The book presents some practical application for securing the CPS as well as building the digital twin of the physical twin of CPS. The digital twin is expected to be one of the pillars for next generation of CPS. Hence, this book provides timely coverage of building and maintaining the digital twins of CPS.

• The book also provides novel algorithms for handling not just Euclidean data but also non-Euclidean data. These algorithms will thus demonstrate how the next generation of digital twins may be made more cognitive by allowing it to process and extract information from complex and higher dimensional data.

Some of the unique features of the book can be listed as follows:

- Only book covering the data-driven modeling of the CPS utilizing the unique relation between the cyber and the physical domain.
- Coverage of machine learning and artificial intelligence algorithms for datadriven modeling of the CPS.
- Practical use case of the data-driven modeling approach for security and building digital twin of the CPS.
- Well-structured and comprehensive book chapters covering the breadth and depth in data-driven modeling of CPS.

Irvine, CA, USA Irvine, CA, USA Sujit Rokka Chhetri Mohammad Abdullah Al Faruque

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Contents

1	Introduction					
	1.1	Cyber-Physical System				
	1.2	Data-Driven Modeling				
	1.3	Side-Channel Analysis				
	1.4	Book S	Sections			
		1.4.1	Part I: Data-Driven Attack Modeling			
		1.4.2	Part II: Data-Driven Defense of Cyber-Physical Systems			
		1.4.3	Part III: Data-Driven Digital Twin Modeling			
		1.4.4	Part IV: Non-Euclidean Data-Driven Modeling of			
			Cyber-Physical Systems			
	1.5	Summ	ary			
	Refe	rences	······			
Pai	t I D	Oata-Dri	ven Attack Modeling			
2	Data	Data-Driven Attack Modeling Using Acoustic Side-Channel				
	2.1	Introdu	action	1		
		2.1.1	Research Challenges and Contributions	1		
	2.2	Backg	round and Related Work	1		
	2.3	•		1		
		2.3.1	System Description	1		
		2.3.2	Equation of Motion	1		
		2.3.3	Natural Rotor Oscillation Frequency	1		
		2.3.4	Stator Natural Frequency	1		
		2.3.5	Source of Vibration	1		
	2.4	Acous	tic Leakage Analysis	1		
		2.4.1	Side-Channel Leakage Model	1		
		2.4.2	Leakage Quantification	2		
		2.4.3	Leakage Exploitation	2		

xii Contents

	2.5 Attack Model Description			21
		2.5.1	Attack Model	21
		2.5.2	Components of the Attack Model	22
		2.5.3	Attack Model Training and Evaluation	31
	2.6	Results	s for Test Objects	34
		2.6.1	Speed of Printing	34
		2.6.2	The Dimension of the Object	35
		2.6.3	The Complexity of the Object	35
		2.6.4	Reconstruction of a Square	36
		2.6.5	Reconstruction of a Triangle	37
		2.6.6	Case Study: Outline of a Key	37
	2.7	Discus	sion	39
		2.7.1	Technology Variation	39
		2.7.2	Sensor Position	39
		2.7.3	Sensor Number	39
		2.7.4	Dynamic Window	40
		2.7.5	Feature Separation during Multiple Axis	
			Movement and Noise	40
		2.7.6	Target Machine Degradation	40
	2.8		ary	40
	Refe			41
•				4.0
3		_	Driven Attack Model with a Compiler Modification	43
	3.1		action	43
	3.2		Model Description	44
	3.3	_	ller Attack	47
		3.3.1	Profiling Phase	48
		3.3.2	Attack Phase	49
		3.3.3	Compiler Modification	50
		3.3.4	Transformations for Leakage Maximization	51
	3.4	-	mental Results	53
		3.4.1	Accuracy Metric	55
		3.4.2	Mutual Information	56
		3.4.3	Partial Success Rate	58
		3.4.4	Total Success Rate	60
	3.5		sion	61
		3.5.1	Countermeasures	62
	3.6		ary	63
	Refe	rences		63
Da-	.4 TT 1	Data Da	inon Defence of Cohon Dhanical Systems	
			iven Defense of Cyber-Physical Systems	
4			Defense Through Leakage Minimization	67
	4.1		action	67
		4.1.1	Motivation for Leakage-Aware Security Tool	67
		4.1.2	Problem and Challenges	68
		413	Contributions	69

Contents xiii

	4.2	System Modeling		
		4.2.1	Data-driven Leakage Modeling and Quantification	70
		4.2.2	Attack Model	71
		4.2.3	Formulation of Data-Driven Leakage-Aware	
			Optimization Problem	73
		4.2.4	Success Rate of the Adversary	76
	4.3	Experi	mental Results	78
		4.3.1	Mutual Information	79
		4.3.2	Test with Benchmark 3D Models	81
	4.4	Case S	tudy with an Attack Model	85
		4.4.1	Success Rate Calculation	85
		4.4.2	Test Case with Reconstruction	86
	4.5	Discus	sion	87
	4.6	Summa	ary	89
	Refe	rences		89
5	Data	-Driven	Kinetic Cyber-Attack Detection	91
J	5.1		iction	91
	5.1	5.1.1	Motivation	92
		5.1.2	Problem and Challenges	92
		5.1.3	Contributions	93
	5.2		Cyber-Attack Adversary Model	93
	5.3		Method	94
	0.0	5.3.1	Mutual Information	95
		5.3.2	KCAD Architecture	96
		5.3.3	Acoustic Analog Emissions	99
		5.3.4	Performance Metrics	101
	5.4		mental Results	101
		5.4.1	Experimental Setup	101
		5.4.2	Mutual Information Calculation	102
		5.4.3	Model Function Estimation	102
		5.4.4	Results for Detection of Kinetic Attack	104
		5.4.5	Test Case: Base Plate of a Quad Copter	106
	5.5	Discus	sion	107
	5.6	Summa	ary	108
	Refe	rences		108
6	Data	-Driven	Security Analysis Using Generative Adversarial	
	-	_		111
	6.1	Introdu	ection	111
		6.1.1	Research Challenges	112
		6.1.2	Preliminaries	113
		6.1.3	Novel Contributions	114
	6.2		-Based CPPS Security Model	114
	63		Model Generation	116

xiv Contents

	6.4	Case S	tudy and Analysis	118
		6.4.1	<i>G_{CPPS}</i> Generation	119
		6.4.2	Experimental Data Collection	121
		6.4.3	CGAN Modeling	121
		6.4.4	Security Analysis Results	122
	6.5	Summa	ary	125
	Refe	erences		125
Pai	rt III	Data-D	riven Digital Twin Modeling	
7			ta-Driven Digital Twin Modeling	129
,	7.1		action	129
	7.1	7.1.1	Research Challenges.	130
		7.1.2	Contributions	130
		7.1.2	Digital Twin Model	131
	7.2		Twin of Cyber-Physical Additive Manufacturing	131
	1.2	_	1 1	131
		7.2.1	Key Performance Indicators (KPIs)	131
	7.3		ng Digital Twin Updated	135
	7.4	-	ng Digital Twin Opuatedng Digital Twin	136
	7.4	7.4.1	Sensor/Emission Modality Selection	136
		7.4.2	Feature Engineering	136
		7.4.3	Sensor Positioning	137
		7.4.4	Data-Driven Models	138
	7.5		mental Setup	138
	7.5	7.5.1	The Test-Bed	139
		7.5.2	Test 3D Objects	142
		7.5.3	Data Collection	142
		7.5.4	Data Segmentation	144
	7.6		ation and Results for Digital Twin Models	146
	7.0	7.6.1	Digital Twin Models	146
		7.6.2	Aliveness	146
	7.7		ary	151
			шy	152
_				
8			Living Digital Twin Modeling	155
	8.1		action	155
		8.1.1	Research Challenges	156
		8.1.2	Contribution	156
		8.1.3	Motivational Case Study for Multi-Sensor Data	
		0.1.1	Analysis	157
		8.1.4	Related Work	158
	8.2	_	round	159
		8.2.1	Concept Definition	159
		8.2.2	IoT Sensor Data as Side-Channels	160
		8.2.3	Metric for Quality Measurement	161

Contents xv

	8.3	Buildin	g the Digital Twin	161
		8.3.1	DT _{product} Parsing	163
		8.3.2	Feature Extraction	163
		8.3.3	Synchronize and Segment	163
		8.3.4	Clustering Algorithm	164
		8.3.5	Anomaly Localization Algorithm	165
		8.3.6	Digital Twin Update Algorithm	165
		8.3.7	Quality Inference Model	166
	8.4	Experin	nental Setup	167
		8.4.1	IoT Sensors	167
		8.4.2	Digital Twin Parameters	169
		8.4.3	Sensor Position Analysis	169
		8.4.4	Performance of Clustering Algorithms	171
		8.4.5	Anomaly Localization Accuracy	171
		8.4.6	System Degradation Prediction Analysis	174
		8.4.7	Quality Inference	176
		8.4.8	Comparative Analysis	177
	8.5	Discuss	sion	179
	8.6	Summa	ry	180
	Refer		······	181
Don	4 TX7	Non Em	olidoon Doto Drivon Modeling of Cyber Physical	
Par 9	Non-	Systems euclidea	n Data-Driven Modeling Using Graph	
	Non-c	Systems euclidear olutiona	n Data-Driven Modeling Using Graph l Neural Networks	185
	Non-6 Conv 9.1	Systems euclidear olutiona Introdu	n Data-Driven Modeling Using Graph l Neural Networks	185
	Non-6 Conve 9.1 9.2	Systems euclidear olutiona Introdu Related	n Data-Driven Modeling Using Graph I Neural Networks ction	185 186
	Non-6 Conv 9.1	Systems euclidean olutiona Introdu Related Graph I	n Data-Driven Modeling Using Graph I Neural Networks ction	185 186 187
	Non-6 Conve 9.1 9.2	Systems euclidean olutiona Introdu Related Graph I 9.3.1	n Data-Driven Modeling Using Graph I Neural Networks ction Work Learning Using Convolutional Neural Network Knowledge Graph Extraction	185 186 187 188
	Non-6 Conve 9.1 9.2	Systems euclidear olutiona Introdu Related Graph I 9.3.1 9.3.2	n Data-Driven Modeling Using Graph l Neural Networks ction l Work Learning Using Convolutional Neural Network Knowledge Graph Extraction Attribute Embedding	185 186 187 188 189
	Non-6 Conve 9.1 9.2	Systems euclidear olutiona Introdu Related Graph I 9.3.1 9.3.2 9.3.3	n Data-Driven Modeling Using Graph I Neural Networks ction Work Learning Using Convolutional Neural Network Knowledge Graph Extraction Attribute Embedding Neighbor Nodes Aggregation	185 186 187 188
	Non-6 Conve 9.1 9.2	Systems euclidear olutiona Introdu Related Graph I 9.3.1 9.3.2	n Data-Driven Modeling Using Graph I Neural Networks ction Work Learning Using Convolutional Neural Network Knowledge Graph Extraction Attribute Embedding Neighbor Nodes Aggregation Structural Graph Convolutional Neural Network	185 186 187 188 189
	Non-6 Conve 9.1 9.2	Systems euclidear olutiona Introdu Related Graph I 9.3.1 9.3.2 9.3.3 9.3.4	n Data-Driven Modeling Using Graph I Neural Networks ction Work Learning Using Convolutional Neural Network Knowledge Graph Extraction Attribute Embedding Neighbor Nodes Aggregation Structural Graph Convolutional Neural Network Layers	185 186 187 188 189 189
	Non-6 Conve 9.1 9.2	Systems euclidean olutiona Introdu Related Graph I 9.3.1 9.3.2 9.3.3 9.3.4	n Data-Driven Modeling Using Graph I Neural Networks ction Work Learning Using Convolutional Neural Network Knowledge Graph Extraction Attribute Embedding Neighbor Nodes Aggregation Structural Graph Convolutional Neural Network Layers Classification for Engineering Design Abstraction	185 186 187 188 189 189
	Non-c Conv 9.1 9.2 9.3	Systems euclidean olutiona Introdu Related Graph I 9.3.1 9.3.2 9.3.3 9.3.4 9.3.5 9.3.6	n Data-Driven Modeling Using Graph l Neural Networks ction Work Learning Using Convolutional Neural Network Knowledge Graph Extraction Attribute Embedding Neighbor Nodes Aggregation Structural Graph Convolutional Neural Network Layers Classification for Engineering Design Abstraction Graph Learning Algorithm Hyper-Parameters	185 186 187 188 189 189 192 197
	Non-c Conv 9.1 9.2 9.3	Systems euclidean olutiona Introdu Related Graph I 9.3.1 9.3.2 9.3.3 9.3.4 9.3.5 9.3.6 GrabCA	n Data-Driven Modeling Using Graph I Neural Networks ction Work Learning Using Convolutional Neural Network Knowledge Graph Extraction Attribute Embedding Neighbor Nodes Aggregation Structural Graph Convolutional Neural Network Layers Classification for Engineering Design Abstraction Graph Learning Algorithm Hyper-Parameters AD Dataset	185 186 187 188 189 189 192 197 197
	Non-c Conv 9.1 9.2 9.3	Systems euclidean olutiona Introdu Related Graph I 9.3.1 9.3.2 9.3.3 9.3.4 9.3.5 9.3.6 GrabCA Results	n Data-Driven Modeling Using Graph l Neural Networks ction Work Learning Using Convolutional Neural Network Knowledge Graph Extraction Attribute Embedding Neighbor Nodes Aggregation Structural Graph Convolutional Neural Network Layers Classification for Engineering Design Abstraction Graph Learning Algorithm Hyper-Parameters AD Dataset	185 186 187 188 189 189 192 197 198 199
	Non-c Conv 9.1 9.2 9.3	Systems euclidean olutiona Introdu Related Graph I 9.3.1 9.3.2 9.3.3 9.3.4 9.3.5 9.3.6 GrabCA Results 9.5.1	n Data-Driven Modeling Using Graph I Neural Networks ction Work Learning Using Convolutional Neural Network Knowledge Graph Extraction Attribute Embedding Neighbor Nodes Aggregation Structural Graph Convolutional Neural Network Layers Classification for Engineering Design Abstraction Graph Learning Algorithm Hyper-Parameters AD Dataset Activation Functions	185 186 187 188 189 192 197 197 198 199 201
	Non-c Conv 9.1 9.2 9.3	Systems euclidean olutiona Introdu Related Graph I 9.3.1 9.3.2 9.3.3 9.3.4 9.3.5 9.3.6 GrabCA Results 9.5.1 9.5.2	n Data-Driven Modeling Using Graph I Neural Networks ction Work Learning Using Convolutional Neural Network Knowledge Graph Extraction Attribute Embedding Neighbor Nodes Aggregation Structural Graph Convolutional Neural Network Layers Classification for Engineering Design Abstraction Graph Learning Algorithm Hyper-Parameters AD Dataset Activation Functions Kernel Size	185 186 187 188 189 189 197 197 198 199 201 201
	Non-c Conv 9.1 9.2 9.3	Systems euclidean olutiona Introdu Related Graph I 9.3.1 9.3.2 9.3.3 9.3.4 9.3.5 9.3.6 GrabCA Results 9.5.1 9.5.2 9.5.3	n Data-Driven Modeling Using Graph I Neural Networks ction Work Learning Using Convolutional Neural Network Knowledge Graph Extraction Attribute Embedding Neighbor Nodes Aggregation Structural Graph Convolutional Neural Network Layers Classification for Engineering Design Abstraction Graph Learning Algorithm Hyper-Parameters AD Dataset Activation Functions Kernel Size Dropout	185 186 187 188 189 192 197 197 198 199 201 201 202
	Non-c Conv 9.1 9.2 9.3	Systems euclidean olutiona Introdu Related Graph I 9.3.1 9.3.2 9.3.3 9.3.4 9.3.5 9.3.6 GrabCA Results 9.5.1 9.5.2 9.5.3 9.5.4	n Data-Driven Modeling Using Graph l Neural Networks ction l Work Learning Using Convolutional Neural Network Knowledge Graph Extraction Attribute Embedding Neighbor Nodes Aggregation Structural Graph Convolutional Neural Network Layers Classification for Engineering Design Abstraction Graph Learning Algorithm Hyper-Parameters AD Dataset Activation Functions Kernel Size Dropout Layers	185 186 187 188 189 192 197 197 198 199 201 201 202 203
	Non-c Conv 9.1 9.2 9.3 9.4 9.5	Systems euclidean olutiona Introdu Related Graph I 9.3.1 9.3.2 9.3.3 9.3.4 9.3.5 9.3.6 GrabCA Results 9.5.1 9.5.2 9.5.3 9.5.4 Discuss	n Data-Driven Modeling Using Graph l Neural Networks ction l Work Learning Using Convolutional Neural Network Knowledge Graph Extraction Attribute Embedding Neighbor Nodes Aggregation Structural Graph Convolutional Neural Network Layers Classification for Engineering Design Abstraction Graph Learning Algorithm Hyper-Parameters AD Dataset Activation Functions Kernel Size Dropout Layers sion	185 186 187 188 189 192 197 197 198 199 201 201 202 203 204
	Non-c Conv 9.1 9.2 9.3 9.4 9.5	Systems euclidean olutiona Introdu Related Graph I 9.3.1 9.3.2 9.3.3 9.3.4 9.3.5 9.3.6 GrabCA Results 9.5.1 9.5.2 9.5.3 9.5.4 Discuss Summa	n Data-Driven Modeling Using Graph l Neural Networks ction l Work Learning Using Convolutional Neural Network Knowledge Graph Extraction Attribute Embedding Neighbor Nodes Aggregation Structural Graph Convolutional Neural Network Layers Classification for Engineering Design Abstraction Graph Learning Algorithm Hyper-Parameters AD Dataset Activation Functions Kernel Size Dropout Layers	185 186 187 188 189 192 197 197 198 199 201 201 202 203

xvi Contents

Dyna	mic Gra	ph Embedding		209
10.1	Introduction			209
	10.1.1	Research Challenges		21
	10.1.2	Contribution		21
10.2	Related	Work		21
	10.2.1	Static Graph Embedding		21
	10.2.2	Dynamic Graph Embedding		21
	10.2.3	Dynamic Link Prediction		21
10.3	Motivat	ting Example		21
10.4	Method	lology		21
	10.4.1	Problem Statement		21
	10.4.2	dyngraph2vec Algorithm		21
	10.4.3	Optimization		21
10.5	Experin	ments		21
	10.5.1	Datasets		21
	10.5.2	Baselines		22
	10.5.3	Evaluation Metrics		22
10.6	Results	and Analysis		22
	10.6.1	SBM Dataset		22
	10.6.2	Hep-th Dataset		22
	10.6.3	AS Dataset		22
	10.6.4	MAP Exploration		22
	10.6.5	Hyper-Parameter Sensitivity: Lookback		22
	10.6.6	Length of Training Sequence Versus MAP Value		22
10.7	Discuss	sion		22
10.8	Summa	ry		22
				22