From inference to influence: applying causal game theory to complex security environments

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Appendix A

Acronyms and Notation Conventions

A.1 Acronyms

A unified list of acronyms that are frequently used throughout the thesis is presented in this section. It includes terms frequently encountered in the context of causal game theory, as well as those related to the methodology introduced in Chapter 5, such as discretization, decision diagrams, and optimization.

ADMG Acyclic Directed Mixed Graph
ATE Average Treatment Effect
BDD Binary Decision Diagram
BN Bayesian Network
BP Belief Propagation
CAIM Class-Attribute Interdependence Maximization
CBN Causal Bayesian Network
CM ChiMerge
CNF Conjunctive Normal Form
CPDAG Completed Partially Directed Acyclic Graph
CPT Conditional Probability Table
DAG Directed Acyclic Graph
DDN Dynamic Discretization
DE Differential Evolution

EBP Bayesian Method with Adjusted Empirical Bayes Priors
EF Equal Frequency
EFG Extensive-Form Game
EW Equal Width
FFRCISTGS Finest Fully Randomized Causally Interpretable Structured Tree Graph
GES Greedy Equivalent Search
ID Influence Diagram
LiNGAM Linear Non-Gaussian Acyclic Model
MAID Multi-Agent Influence Diagram
MDLP Minimum Description Length Principle
MLE Maximum Likelihood Estimation
NFG Normal-Form Game
NPSEM-ie Non-Parametric Structural Equation Model with Independent Errors
PE ATE Percentage Error of the Average Treatment Effect
PGM Probabilistic Graphical Model
PO Potential Outcome
POF Potential Outcome Framework
RCT Randomized Controlled Trial
SCM Structural Causal Model
SEM Structural Equation Model
SESEM Spatially Explicit Structural Equation Model
SPE Subgame Perfect Equilibrium
SUTVA Stable Unit-Treatment Value Assumption
SWIG Single World Intervention Graph
VE Variable Elimination
WRMSE Weighted Root Mean Squared Error

A.2 Notation Conventions

The notation conventions that are used throughout this thesis can be found in Table A.1.

Table A.1: List of Frequently Used Notation Conventions

Symbol	Object
$\boldsymbol{A}$	Set of Action Sets
B_j	Discretized Bin
Γ	Game
$\mathbf{ch}(V_i)$	Children of Node V_i
$\boldsymbol{D}$	Set of Decision Nodes
do	Do-Operator
$\mathbf{de}(V_i)$	Descendants of Node V_i
$\boldsymbol{E}$	Set of Edges
$\mathbb{E}[X_i]$	Expected Value of X_i
$\boldsymbol{F}$	Set of Structural Functions
$\mathcal{G}$	Family of Graphs
G	Graph
G_i	Subgraph of Nodes V_j, where $j \leq i$ in the Topological Sort
$G_{\overline{\boldsymbol{V'}}}$	Mutilated Graph G with respect to $\overline{\boldsymbol{V'}}$
M	Agents
μ_i	Higher-Order Belief
$\mathbf{nonde}(V_i)$	Non-Descendants of Node V_i
ρ	Path
$\mathbf{pa}(V_i)$	Parents of Node V_i as Random Variables
$\boldsymbol{pa}_i$	Assignments of Parents of Node V_i
$P(X_i)$, $p(X_i)$	Probability Distribution of X_i (Discrete or Continuous)
$\mathcal{S}$	Structural Causal Model
σ^i	Strategy
σ	Strategy Profile
σ^{-i}	Partial Strategy
T	Treatment Variable or Type Profile Tuple
$\boldsymbol{U}$	Set of Utilities
$\boldsymbol{V}$	Set of Nodes
$\boldsymbol{W}$	Set of Exogenous Variables
$\boldsymbol{X}$	Set of Random Variables
X_i	Random Variable
$\boldsymbol{X}_{-i}$	Random Variables $\boldsymbol{X} \setminus X_i$
$\boldsymbol{x}$, x_i	Assignment of $\boldsymbol{X}$, X_i
Y	Dependent or Outcome Variable
Ω	State Space
Ω_{X_i}	State Space of Random Variable X_i
$\perp\!\!\!\perp_P$	Independence in Probability
$\perp\!\!\!\perp_G$	d-separation
$<$	Ordering induced by Topological Sort

Appendix B

Appendix Chapter 5

B.1 Heatmap Results

As the computational cost becomes generally higher when the number of bins in the discretization process increases, the heatmaps in this section focus on the quality of discretization and inference. For example, the discretization EF9 in Pareto front of Figure 5.5e dominates all other EF discretizations in terms of the error. Therefore, EF9 returns in the heatmap of Table B.1 in the corresponding error and CPT inference method column.

Table B.1: Heatmap summarizing the causal results: every box refers to a Pareto front corresponding to discretization methods EF and EB, evaluation measure EMD, WRMSE and PE ATE, and inferring CPT method MLE or EBP. The color indicates the number of bins in the best approach for the corresponding experiment with respect to the chosen evaluation measure: light blue stands for a small number of bins and dark blue means a large number of bins. In the heatmap, a star indicates MDLP dominance over all solutions for that binning strategy, a plus signifies CAIM dominance, a minus denotes ChiMerge dominance and a tilde denotes dynamic discretization dominance.

	Error measure	EMD	PE ATE	
	CPT method	All	EBP	
	Binning method	–	EF	EW
Experiment	*N*			
CQ DGP	2500	EF30	EF30	EW25
Lalonde	2675	EF12	EF9*	EW3*
MC	4000	EW30		

Table B.2: Heatmap summarizing all the non-causal results.

Error measure		EMD	WRMSE			
CPT method		NA	EBP	MLE	EBP	MLE
Binning method		All	EF	EF	EW	EW
Experiment	N					
LG9	5000	EF30	EF17	EF17	EW12	EW12*
LG10	3000	EF30	EF17*	EF17*	EW10*	EW10*
LG11	2000	EF30	EF12*	EF12*	EW8*	EW8*
LG12	1000	EF30	EF12	EF12	EW8*	EW8*
LG13	800	EF30	EF12	EF12	EW5*	EW5*
LG14	600	EW30	EF8	EF8	EW8*	EW8*
LG15	500	EW30	EF8	EF8	EW8*	EW8*
LG16	400	EW30	EF8	EF8	EW5*	EW5*
LG17	300	EW30	EF8	EF8	EW5*	EW5*
LG18	200	EW30	EF5	EF5	EW5-	EW5-
LG19	100	EW30	EF5	EF5	EW5-	EW5-
LG101	100	EW30	EF5	EF5	EW8*	EW8*
LG102	1050	EF30	EF12	EF12	EW8	EW8
LG103	1525	EF30	EF12	EF12	EW10*	EW10*
LG104	575	EF30	EF5*	EF5*	EW5*	EW5*
LG105	812	EF30	EF12	EF12	EW8*	EW8*
LG106	1762	EF30	EF17	EF17	EW8*	EW8*
LG107	1288	EF30	EF12	EF12	EW8*	EW8*
LG108	338	EW30	EF8	EF8	EW5-	EW5-
LG109	456	EW30	EF8	EF8	EW5*	EW5*
LG110	1406	EF30	EF10	EF10	EW8-	EW8-
LG111	1881	EF30	EF10*	EF10*	EW12*	EW12*
LG112	931	EF30	EF10	EF10	EW5*	EW5*
LG113	694	EW30	EF10	EF10	EW8*	EW8*
LG114	1644	EW30	EF14	EF14	EW8-	EW8-
LG115	1169	EF30	EF12	EF12	EW10*	EW10*
LG116	219	EW30	EF5	EF5	EW5-	EW5-
LG117	278	EW30	EF5	EF5	EW5-	EW5-
LG118	1228	EF30	EF10	EF10	EW8*	EW8*
LG119	1703	EF30	EF17	EF17	EW10*	EW10*
LG120	753	EF30	EF12	EF12	EW8-	EW8-
LG121	991	EF30	EF12*	EF12*	EW8*	EW8*
LG122	1941	EF30	EF10	EF10	EW8*	EW8*
LG123	1466	EF30	EF12	EF12	EW8*	EW8*
LG124	516	EW30	EF10	EF10	EW5*	EW5*
LG125	397	EW30	EF8	EF8	EW5*	EW5*
NM1	500	EW30+	EF25+	EF25+	EW20+	EW20+
NM2	500	EF30+	EF30+	EF30+	EW30+	EW30+
NM3	500	EF30+	EF25+	EF25+	EW17+	EW17+
NM4	500	EF30+	EF30+	EF30+	EW25+	EW25+
NM5	100	EF30+	EF8+	EF8+	EW17+	EW17+
NM6	100	EF30+	EF30+	EF30+	EW25+	EW25+
NM7	100	EF30+	EF17+	EF17+	EW30+	EW30+
NM8	100	EF25+	EF25+	EF25+	EW30+	EW30+
Arth	1000	EW30				

B.2 Experimental Set-up

The experimental setup outlines the specifications of each of the experiments in terms of their distribution and sample size.

Table B.3: The first 25 experiments involving linear Gaussian BNs parameterized by Sobol sequences for the number of samples N and standard deviations. Each variable follows a normal distribution $\mathcal{N}(\mu, \sigma)$, with mean μ specified in the header and standard deviation σ listed in the table.

		$P(X_1)$	$P(X_2)$	$P(X_3)$	$P(X_4 \mid X_1, X_2)$	$P(X_5 \mid X_3, X_4)$
	μ	20	20	15	$2X_1 + 3X_2$	$3X_3 + 3X_4$
Experiment	N	σ	σ	σ	σ	σ
LG101	100	1	1	1	1	1
LG102	1050	5.5	5.5	5.5	5.5	5.5
LG103	1525	3.25	3.25	3.25	3.25	3.25
LG104	575	7.75	7.75	7.75	7.75	7.75
LG105	813	4.38	4.38	4.38	4.38	4.38
LG106	1763	8.88	8.88	8.88	8.88	8.88
LG107	1288	2.13	2.13	2.13	2.13	2.13
LG108	338	6.63	6.63	6.63	6.63	6.63
LG109	456	3.81	3.81	3.81	3.81	3.81
LG110	1406	8.31	8.31	8.31	8.31	8.31
LG111	1881	1.56	1.56	1.56	1.56	1.56
LG112	931	6.06	6.06	6.06	6.06	6.06
LG113	694	2.69	2.69	2.69	2.69	2.69
LG114	1644	7.19	7.19	7.19	7.19	7.19
LG115	1169	4.94	4.94	4.94	4.94	4.94
LG116	219	9.44	9.44	9.44	9.44	9.44
LG117	278	5.22	5.22	5.22	5.22	5.22
LG118	1228	9.72	9.72	9.72	9.72	9.72
LG119	1703	2.97	2.97	2.97	2.97	2.97
LG120	754	7.47	7.47	7.47	7.47	7.47
LG121	991	1.84	1.84	1.84	1.84	1.84
LG122	1941	6.34	6.34	6.34	6.34	6.34
LG123	1466	4.09	4.09	4.09	4.09	4.09
LG124	516	8.59	8.59	8.59	8.59	8.59
LG125	397	2.41	2.41	2.41	2.41	2.41

Table B.4: Number of samples and parametrization of the experiments with the 11 extra linear Gaussian Bayesian networks. These experiments are meant to isolate the effect of the sample size on the Pareto front. Note that the samples in lower sample-sized experiments are contained in the samples of experiments with higher sample sizes.

(a) Parametrization of all of the experiments

$P(X_1)$	$P(X_2)$	$P(X_3)$	$P(X_4 \mid X_1, X_2)$	$P(X_5 \mid X_3, X_4)$
$\mathcal{N}(20, 2)$	$\mathcal{N}(20, 2)$	$\mathcal{N}(15, 2)$	$\mathcal{N}(2X_1 + 3X_2, 2)$	$\mathcal{N}(3X_3 + 3X_4, 2)$

(b) Name and sample size of experiments

Experiment	**LG9**	**LG10**	**LG11**	**LG12**	**LG13**	**LG14**	**LG15**	**LG16**	**LG17**	**LG18**	**LG19**
N	5000	3000	2000	1000	800	600	500	400	300	200	100

Table B.5: Name, number of samples, and parametrization of the experiments with the Normal mixture model

Experiment	N	$P(X_1)$	$P(X_2 \mid X_1 = 1)$	$P(X_2 \mid X_1 = 0)$
NM1	500	$B(1, \frac{1}{2})$	$\mathcal{N}(21, 10)$	$\mathcal{N}(25, 1)$
NM2	500	$B(1, \frac{4}{5})$	$\mathcal{N}(21, 10)$	$\mathcal{N}(25, 1)$
NM3	500	$B(1, \frac{1}{2})$	$\mathcal{N}(6, 2)$	$\mathcal{N}(4, 2)$
NM4	500	$B(1, \frac{4}{5})$	$\mathcal{N}(6, 2)$	$\mathcal{N}(4, 2)$
NM5	100	$B(1, \frac{1}{2})$	$\mathcal{N}(21, 10)$	$\mathcal{N}(25, 1)$
NM6	100	$B(1, \frac{4}{5})$	$\mathcal{N}(21, 10)$	$\mathcal{N}(25, 1)$
NM7	100	$B(1, \frac{1}{2})$	$\mathcal{N}(6, 2)$	$\mathcal{N}(4, 2)$
NM8	100	$B(1, \frac{4}{5})$	$\mathcal{N}(6, 2)$	$\mathcal{N}(4, 2)$

The following causal quadratic (CQ) experiment is adopted from Parikh et al. [176]:

$$\begin{aligned}
&X_i \sim \mathcal{N}(0, 1) \\
&Y_i(0) = \beta^T X_i + \epsilon_0 && \text{where } \epsilon_0 \sim \mathcal{N}(0, 1) \\
&Y_i(1) = Y_i(0)^2 + \alpha^T X_i + \epsilon_1 && \text{where } \epsilon_1 \sim \mathcal{N}(0, 1) \\
&T_i = \text{expit}(\mathbf{1}^T X_i))
\end{aligned}$$

A maximum number of 30 bins was allowed for all experiments except for the Lalonde dataset (12 bins maximum).

B.3 Evaluation Measures

The conditional expected value of the target variable, $\mathbb{E}[Y \mid X]$, in the original Bayesian network is compared with its counterpart in the discretised network, denoted $\mathbb{E}_{\text{disc}}[Y \mid X]$, where X is a root node. To account for the distribution of X, the accuracy of the discretized expectation is assessed using the weighted root mean squared error (WRMSE):

$$WRMSE = \sqrt{\sum_{x} P(X = x)(\mathbb{E}[Y \mid X = x] - \mathbb{E}_{disc}[Y \mid X = x])^2}$$

where $P(X = x)$ denotes the discretized probability that X takes value x. Note that the number of values involved in WRMSE depends on the discretization of the root node X.

For the causal Bayesian networks in Section 5.3.2, the average treatment effect is obtained using the adjustment formula detailed in Chapter 3. The experiments investigate the percentage error (PE) of the average treatment effect (ATE) as the primary object of analysis:

$$PE = 100 \times \left| \frac{ATE_{true} + ATE_{disc}}{ATE_{true}} \right| .$$

Appendix C

Appendix Chapter 6

C.1 Experimental Data of Deterring Hybrid Threat

This section specifies the details about the experiments of the experimental section by specifying the probability distributions these experiments are drawn from.

The most damaging impact θ_1 and the substantial impact θ_2 are drawn from the truncated normal distributions $f(x, \mu_1, \sigma_1, a, b)$ and $f(x, \mu_2, \sigma_2, a, b)$ respectively, where $a = 0$, $\mu_1, \mu_2 = 1000, 100$ and $\sigma_1, \sigma_2 = 300, 50$ respectively [170]. Hence x is drawn from the interval $[0, \infty]$. Negligible damaging impact θ_3 is drawn from a positive half-normal distribution based on normal distribution $\mathcal{N}(0, 5)$. All values represent millions of damaging costs.

The costs γ_i for each of the counter-hybrid measures d_i are drawn from truncated normal distributions. The probability of the adversary conducting a hybrid operation q_{ij} after counter-hybrid measure d_i is drawn from beta distributions as it is the conjugate prior to the Bernoulli distribution (assuming the adversary either attacks or does not attack). Finally, the probabilities of the potential impact of hybrid conduct w_{ijh} based on counter-hybrid measure d_i and attack c_j are drawn from a Dirichlet distribution as it is the conjugate prior to the categorical distribution and commonly used in influence diagrams [228].

Active intelligence sharing. When intelligence is shared, this is not directly communicated to the adversary, leaving the probability that the adversary conducts a hybrid operation after this measure q_{11} at $Be(5, 5)$. However, this measure significantly improves the mitigation ability of the damaging impact of the hybrid conduct leaving the probabilities being drawn from Dirichlet distribution:

$$\begin{pmatrix} w_{111} \\ w_{112} \\ w_{113} \end{pmatrix} \sim \text{Dir} \begin{pmatrix} 4 \\ 8 \\ 12 \end{pmatrix}.$$

The cost of this measure accounts for losing confidential information to unauthorized parties and is drawn from the truncated normal distributions $f(x, \mu, \sigma, a, b)$ with $\mu = 150, \sigma = 50$ and $a = 0$. In case the adversary does not conduct a hybrid operation, the probability that the damaging impact will be negligible is always 1.

Boost cyber resilience at the wider societal level. Boosting cyber resilience works via deterrence by denial, leaving the probability that the measure dissuades the adversary from committing a hybrid conduct q_{21} drawn from $Be(4, 8)$ and the mitigation of potential impact drawn from the following Dirichlet distributions:

$$\begin{pmatrix} w_{211} \\ w_{212} \\ w_{213} \end{pmatrix} \sim \text{Dir} \begin{pmatrix} 3 \\ 5 \\ 8 \end{pmatrix}.$$

The cost of this measure is mostly carried by the private sector and is drawn from truncated normal distribution $f(x, \mu, \sigma, a, b)$ with $\mu = 300, \sigma = 50$ and $a = 0$.

Offensive cyber operation. An offensive cyber operation has deterrence by denial as well as deterrence by punishment components. To compensate for the fact that the measure can also backfire, the probability that this measure is successful in dissuading the adversary from committing hybrid conduct q_{31} is drawn from $Be(1, 1.2)$ and the damage mitigation potential drawn from the following Dirichlet distributions:

$$\begin{pmatrix} w_{311} \\ w_{312} \\ w_{313} \end{pmatrix} \sim \text{Dir} \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix}.$$

The costs of this measure contain the cost of setting up an offensive cyber unit as well as the cost that comes with the associated attack. It is drawn from truncated normal distribution $f(x, \mu, \sigma, a, b)$ with $\mu = 250, \sigma = 30$ and $a = 0$.

Market restriction. Imposing market restrictions works via deterrence by denial and therefore the probability that this counter-hybrid measure dissuades the adversary from committing hybrid conduct q_{41} is drawn from $Be(2, 8)$. The probabilities of potential impacts are drawn from the Dirichlet distribution

$$\begin{pmatrix} w_{411} \\ w_{412} \\ w_{413} \end{pmatrix} \sim \text{Dir} \begin{pmatrix} 2 \\ 2 \\ 15 \end{pmatrix}.$$

Finally, the costs of the measure involve excluding certain private organizations from the market and is drawn from truncated normal distribution $f(x, \mu, \sigma, a, b)$ with $\mu = 400, \sigma = 50$ and $a = 0$.

Open deterrence messaging through strategic communications. Assuming that the message involves some deterrence by punishment and there is uncertainty involved in threatening, the probability that this deterrence measure successfully dissuades the adversary from committing a hybrid conduct q_{51} is drawn from $Be(0.4, 2)$. Damage mitigation is not involved and therefore the probabilities for damaging impacts are drawn from the same Dirichlet distribution as no measure was taken:

$$\begin{pmatrix} w_{511} \\ w_{512} \\ w_{513} \end{pmatrix} \sim \text{Dir} \begin{pmatrix} 12 \\ 6 \\ 2 \end{pmatrix}.$$

Finally, the costs of the measure also include costs of a risky escalation that one commits to and is drawn from truncated normal distribution $f(x, \mu, \sigma, a, b)$ with $\mu = 500, \sigma = 250$ and $a = 0$.

No deterrence measure. Assuming no deterrence measure taken d_6, the probability that the adversary conducts a hybrid operation q_{61} is drawn from $Be(5, 5)$. Similarly, in case the defender does not conduct a deterrence effort and the adversary conducts a hybrid operation the probability of each of the three impacts is drawn from the Dirichlet distribution:

$$\begin{pmatrix} w_{611} \\ w_{612} \\ w_{613} \end{pmatrix} \sim \mathrm{Dir}\begin{pmatrix} 12 \\ 6 \\ 2 \end{pmatrix}.$$

In case the adversary does not conduct a hybrid operation, the probability that the damaging impact will be negligible is always 1.

Figure C.1 and C.2 illustrate the distribution of successful deterrence and the distribution of the potential impact of the malicious cyber attack, respectively.

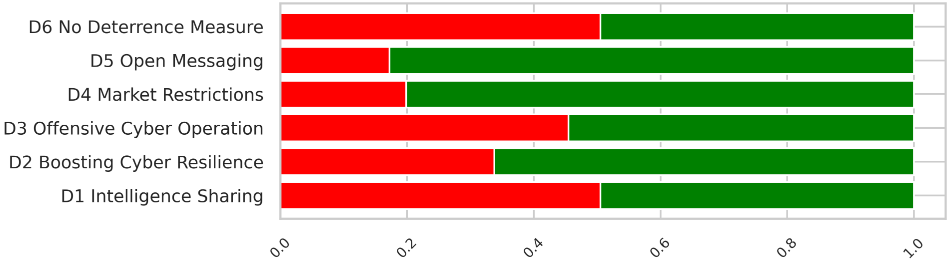

Figure C.1: The probability that each of the counter-hybrid measures succeeds in deterring the adversary sampled from Beta Distribution. While the green indicates the probability that the adversary is successfully dissuaded, the red illustrates the probability that the adversary still conducts a cyber operation.

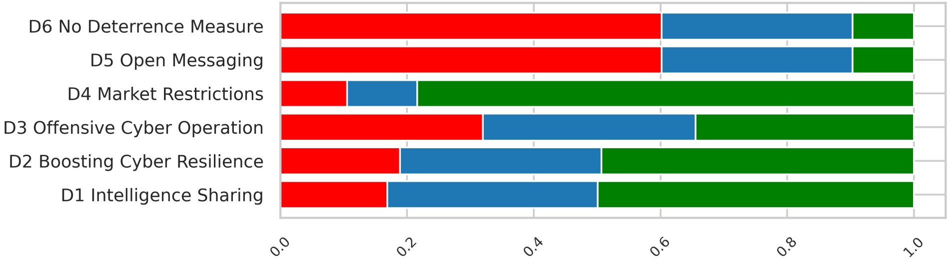

Figure C.2: The probability that each of the counter-hybrid measures succeeds in mitigating the hybrid operation sampled from Dirichlet distribution. While the red indicates the probability the hybrid operation has a severe impact, the blue indicates the operation has a mediocre impact and the green indicates the hybrid operation has negligible impact.

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