

Game Theory Meets Information Security Management

Andrew Fielder
Research Associate
Imperial College London

Overview

- Research Objectives
- Cyber Security Resources
- Model Design
- Game Theoretic Formulation
- Solving The Game
- Experiment Overview
- Results
- Future Work



Research Objectives

- Questions
 - How do we make better security decisions
 - Development of effective strategies by CISOs
 - Optimal Levels of Funding
- Objectives
 - Game Theory to model Complex Scenarios
 - Abstract These Models
 - Build Proof of Concept tools
- Expected Results
 - New Theory and understanding of games in a cyber security environment
 - Empirical evaluation (against real data where possible)
 - New Policy Advice

Cyber Security Resources

Hackmageddon¹:

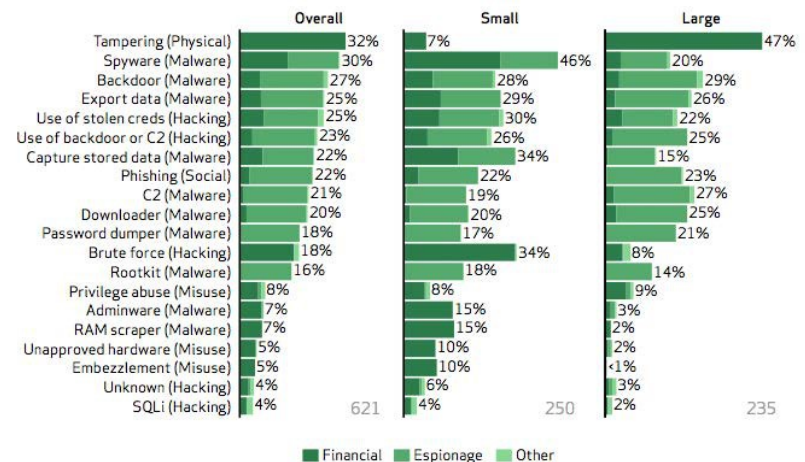
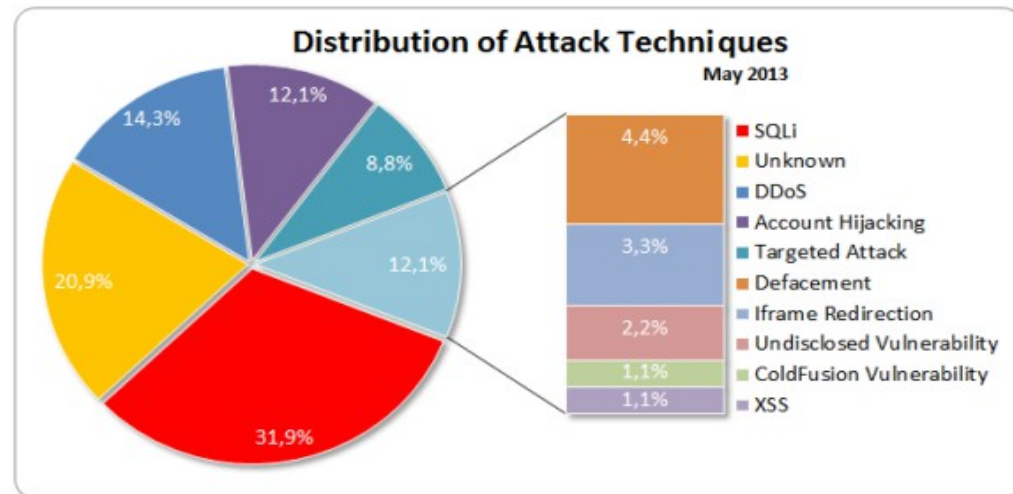
Compiled Statistics from attacks made public.
Current Data Source used in Experiments

Verizon Data Breach Report²:

47,000+ security incidents analysed
621 confirmed data breaches Studied
19 international Contributors

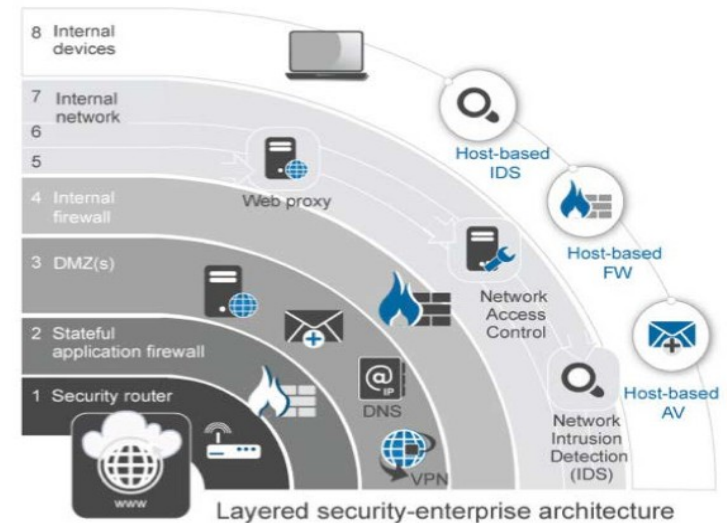
Interviews:

QMUL – Working with an Systems Administrator with SME Experience
Imperial – Attack and Log data available for study

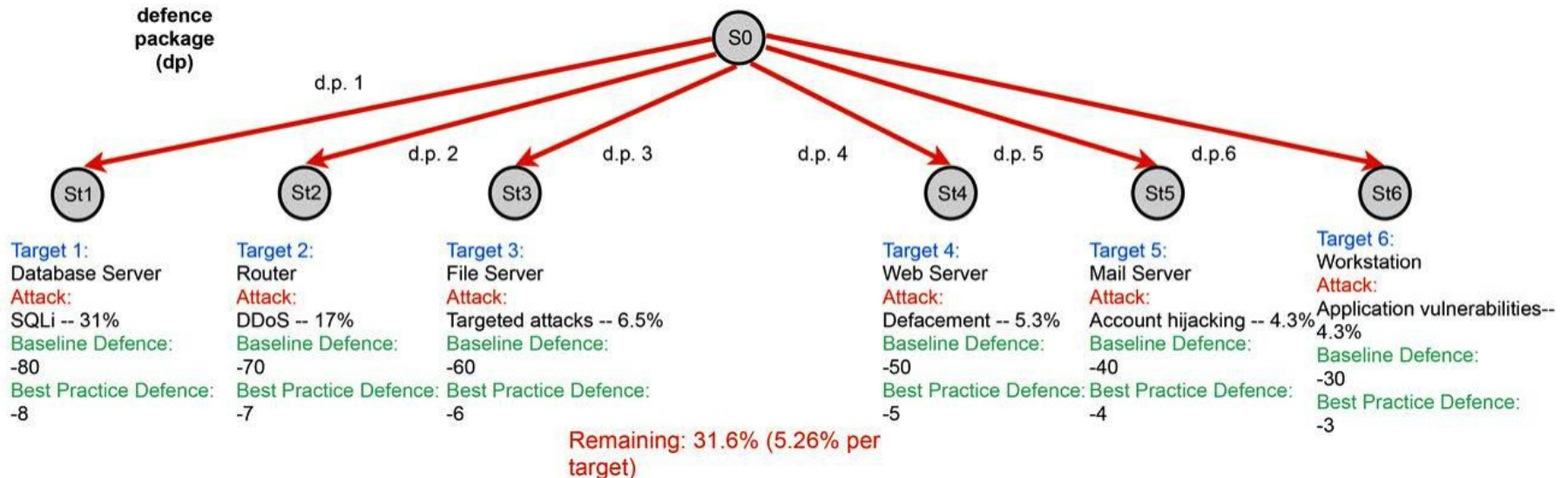


Model Design

- What are our Targets?
 - Data Assets
- How do we consider Attacks?
 - Exploitation of a Vulnerability
 - Unique Path
- How do we consider Defences?
 - All processes for upgrading network defence
- Why do we consider Administrators' Time?



Model Design



- An example of an attack graph that represents the kind of problem we try to solve
 - Paths
 - Targets
 - Defence Packages

Game Theoretic Formulation

- Players
 - Defender \mathcal{D}
 - Attacker \mathcal{A}
- Targets

$$T = t_1, t_2, \dots, t_n$$
- Schedules

$$S \subseteq \{0, 1\}^n$$
- Utilities of Targets
 - BaseLine $U_{\mathcal{D}}^{bl}(t_i)$
 - Best Practice $U_{\mathcal{D}}^{bp}(t_i)$



Game Theoretic Formulation

- Utilities

$$U_{\mathcal{D}}(\mathbf{D}, \mathbf{A}) = \sum_{i=1}^n E_{D,C}(t_i) = \sum_{i=1}^n a_i (c_i U_{\mathcal{D}}^{bp}(t_i) + (1 - c_i) U_{\mathcal{D}}^{bl}(t_i))$$

- Nash Equilibrium

\mathcal{D} plays a best-response that is $U_{\mathcal{D}}(\mathbf{D}, \mathbf{A}) \geq U_{\mathcal{D}}(\mathbf{D}', \mathbf{A}), \forall \mathbf{D}'$

\mathcal{A} plays a best-response that is $U_{\mathcal{A}}(\mathbf{D}, \mathbf{A}) \geq U_{\mathcal{A}}(\mathbf{D}, \mathbf{A}'), \forall \mathbf{A}'$

- Game uses a Perfect Affine Transformation
- Games are general-sum, but min-max solution is equal to Nash.

Solving The Game

- A Python Based Min-Max Solver
- We have used a method based on Singular Value Decomposition (SVD) to compute equilibria in large games where a large number of assets of the defending party must be protected against adversaries.
- Our method provides reasonably close solutions to the original game solutions and a significant speed up of the computation.

Experimental Overview

- We compare the outcome of the Min-Max to Two Common Sense Approaches:
 - Uniform – A Naive Approach, where everything is treated equally and the schedule is evenly spread.
 - Weighted – Schedule Time based on the relative value of the target.
- We additionally compare the Min-Max to a Optimisation Based Approach:
 - AC - An optimisation method that aims to reduce the amount of damage expected.

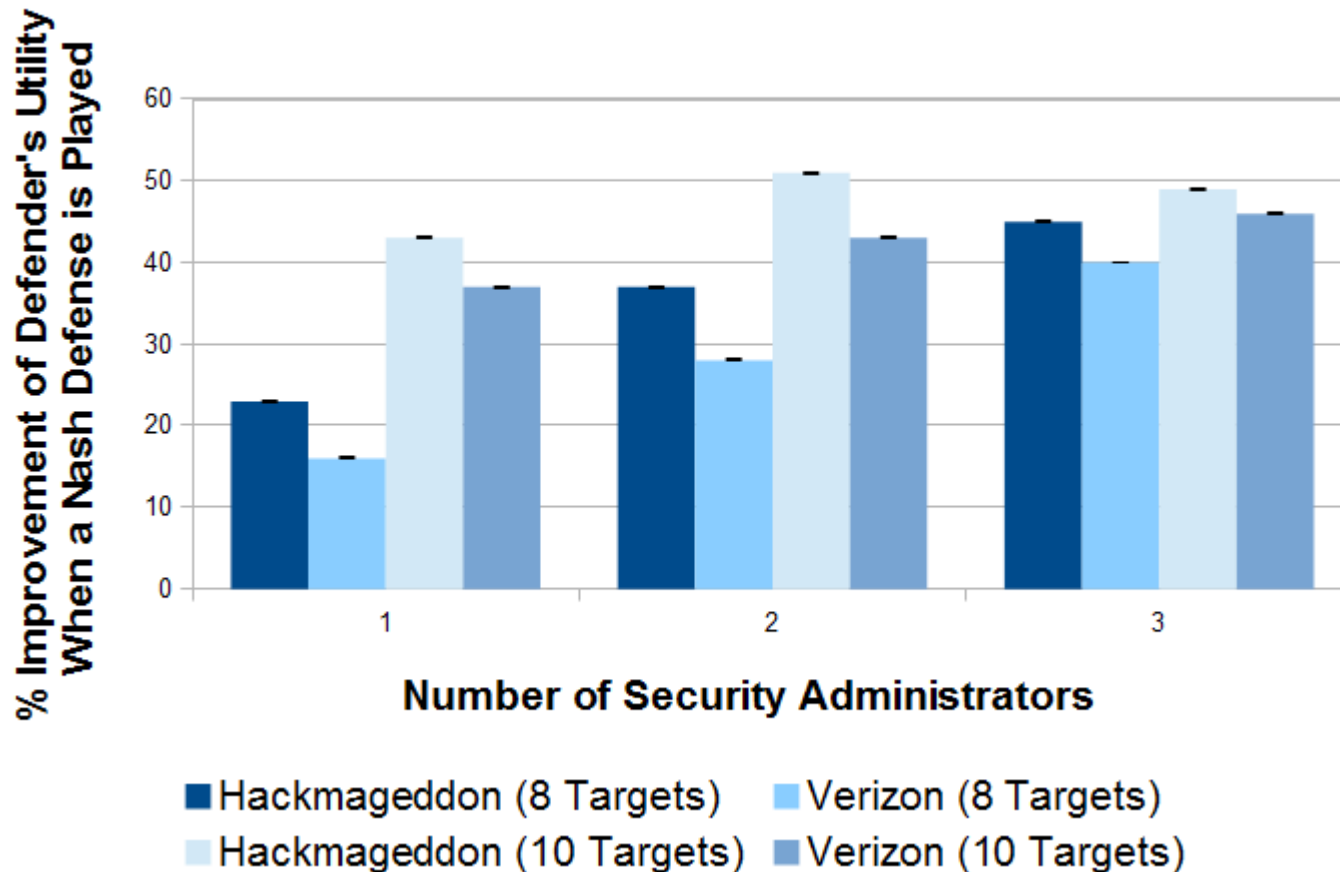
Experimental Overview

- Attack Sets
 - Hackmageddon
 - Verizon Data Breach Report
- Data Loss Costs
 - Ponemon Institute
- Experiment Specific Data
 - Number of Administrators - 1, 2 and 3
 - Number of Targets - 8 and 10
 - Sample Size - 10000 Sample Attacks
- Variance of Asset Utilities



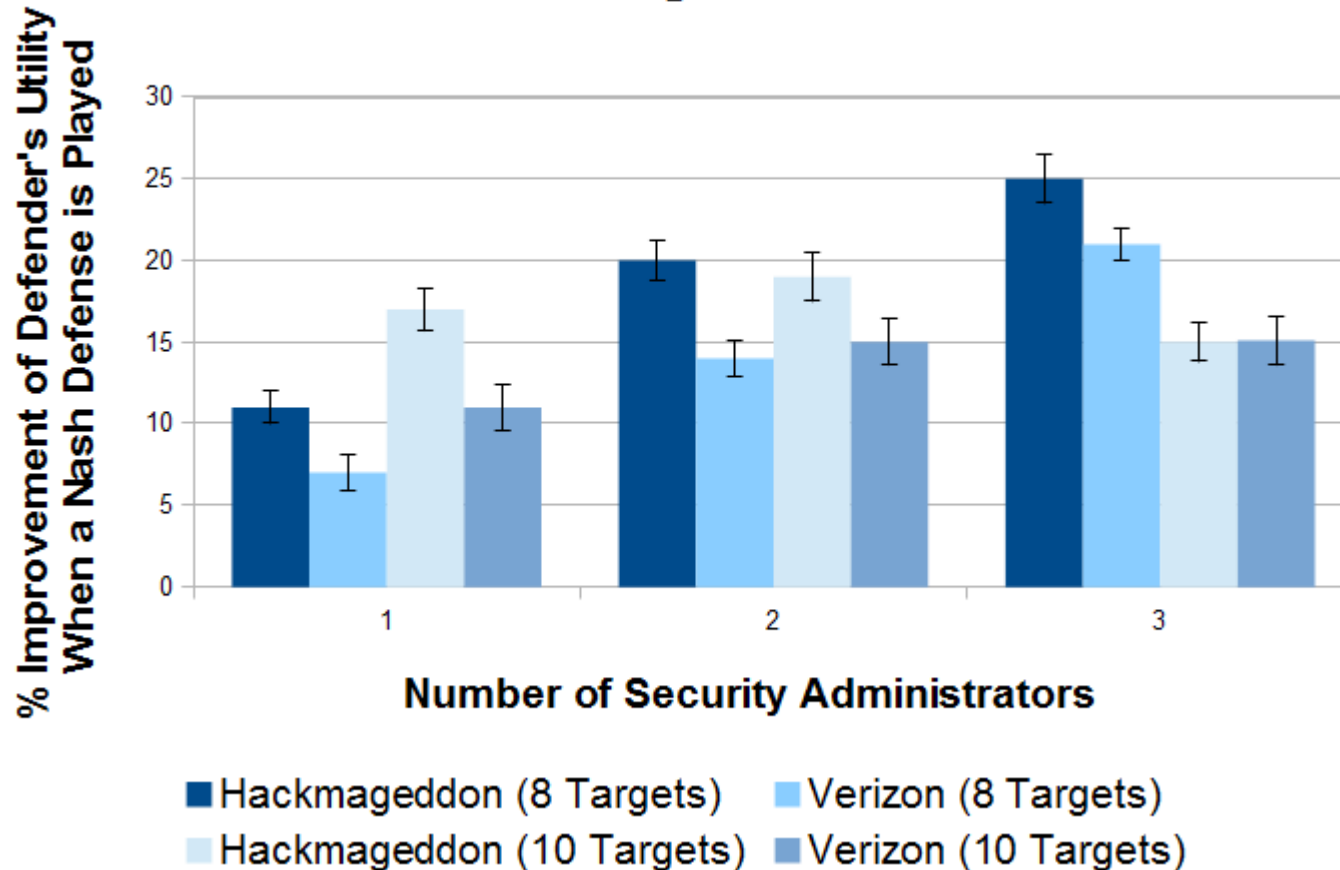
Results

Uniform



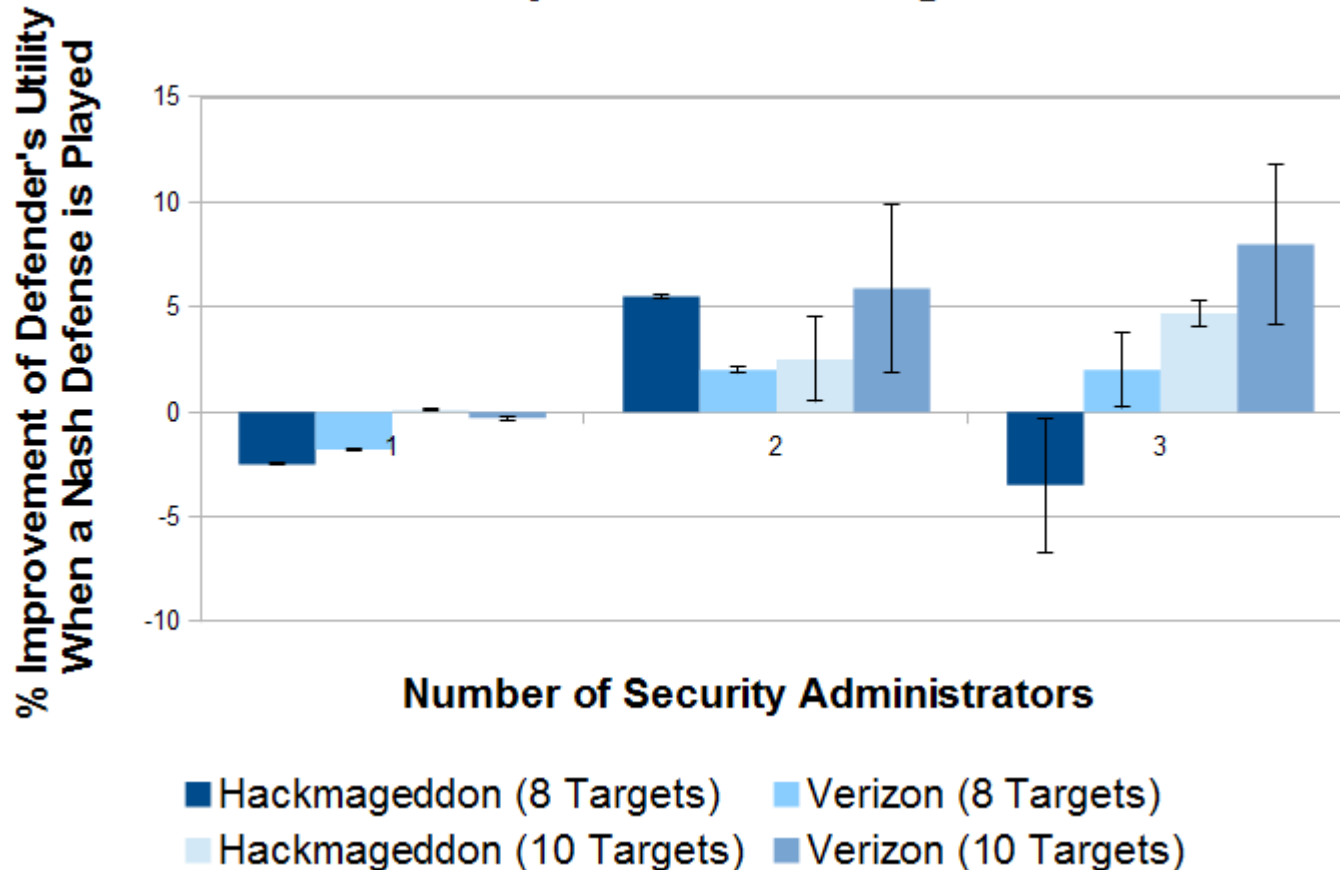
Results

Weighted



Results

Acceptable Coverage



Future Work

- Interdependencies
- Multi-Stage Games
- Development of the model beyond Time
- Looking more towards investment
- Improved Sources of Data

