FIGHTING CYBER-THREATS WITH CROWDSOURCED INTELLIGENCE

ZOHAR DUCHIN, PRINCIPAL RESEARCHER RSA

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Why Are We Loosing The Cyber Arena?

- **Security analysts as lone rangers**
  - Each analyst sees only tiny part of the picture
  - Nobody knows everything
  - Repeating mistakes that others already did

Defenders

Heroic but separated and unorganized

Attackers

Well organized and motivated (organized crime, nation state actors)

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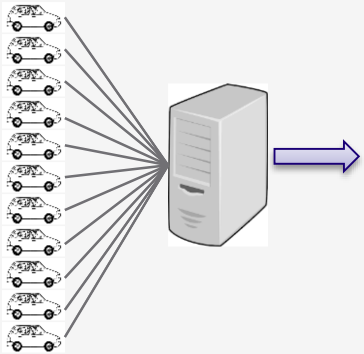
How Can Crowdsourcing Help?

Crowdsourced navigation intelligence

Tiny part of the road from each car

Analytics

Map + prediction + navigation instructions

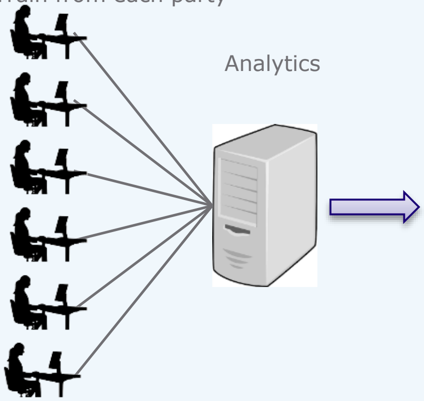


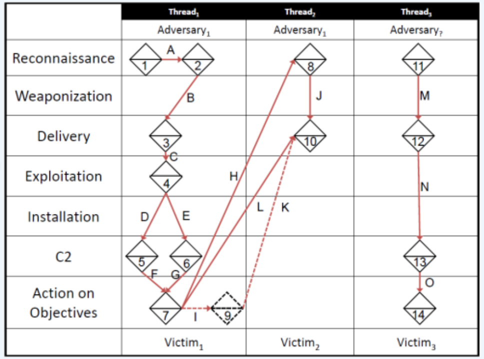
Crowdsourced security intelligence

Tiny part of security terrain from each party

Analytics

Attack threads + predictions + mitigation instructions





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Helping the Analyst with Crowdsourced Intelligence

The analyst daily job

Prioritize

The ask: Help me to focus on the most important events

↓

Investigate and Decide

The ask: Guide me through the investigation process and help me to reach the right decision faster

↓

Remediate and Predict

The ask: Help me to set the right indicators for future protection
Help me to be prepared for attacks am I likely to encounter in the near future

Prioritization with Crowdsourced Intel'

- **Use cases**
  - Others opinion on the same / similar events
  - Trends of same events in the community
  - Overall reputation

- **Example: prioritizing suspicious IP addresses with community reputation**
  - Aggregating feedback from the community
  - Using lower bound interval of Wilson score to be conservative
  - Include time decay as IP addresses are dynamic

$$Score = \frac{\hat{p} + \frac{1}{2n}z^2 - z\sqrt{\frac{\hat{p}(1-\hat{p})}{n} + \frac{z^2}{4n^2}}}{1 + \frac{1}{n}z^2}$$

Where:

- n = total number of customers that have the IP *decayed with time i.e.:*

$$n = \sum_i 1\,\{customer_i\ has\ IP\} * e^{-\Delta t_{ni}/\omega}$$

- $\hat{p} = \frac{\#\ of\ risky}{n}$
- $\#\ of\ risky = \sum_i 1\{customer_i\ \text{provided}\ risky\ feedback\} * e^{-\Delta t_{fi}/\omega}$
- w = Constant that controls the speed of decay
- Δt_{fi} = age of $feedback$ from customer i
- Δt_{ni} = age of IP at customer i
- $z = 1.96$

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Investigation with Crowdsourced Intel’

- **Use cases:**
  - Best practices: Investigation steps that others have taken
  - If I have found this event, what related items should I look for?
  - What is the most valuable information that will help my decision?

- **Example**
  - Filling attack kill chain using various sources in the community
    - Different customers with different detectors
  - Guiding users to investigate the missing link in the chain

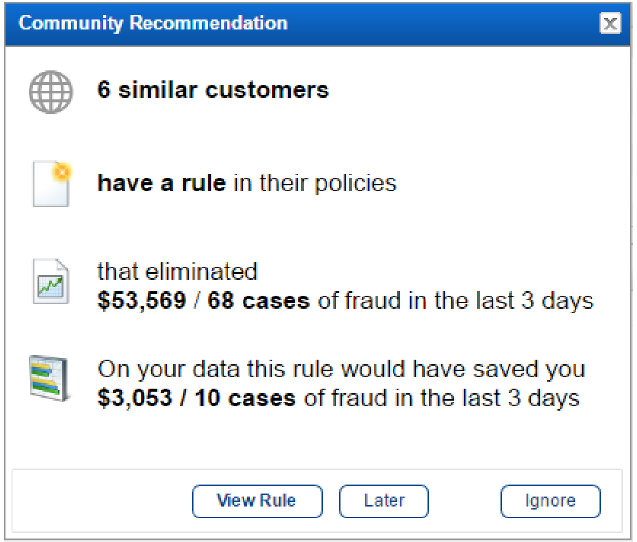
Interacting with contributors to fill missing info

Phase	Indicator	Contributed by
Reconnaissance	NA	
Weaponization	Benign File: tcnom.pdf	User C: Endpoint
Delivery	?	User B: Network
Exploitation	CVE-2009-0658 [shellcode exploiting]	External source
Installation	fssm32.exe IEUpd.exe IEXPLORE.hlp	User A: Endpoint User C: Endpoint
C2	202.abc.xyz.7 [HTTP request]	User B: Network
Actions on Objectives	Key logging	User B: SecOps

Remediate and Predict with Crowdsourced Intel'

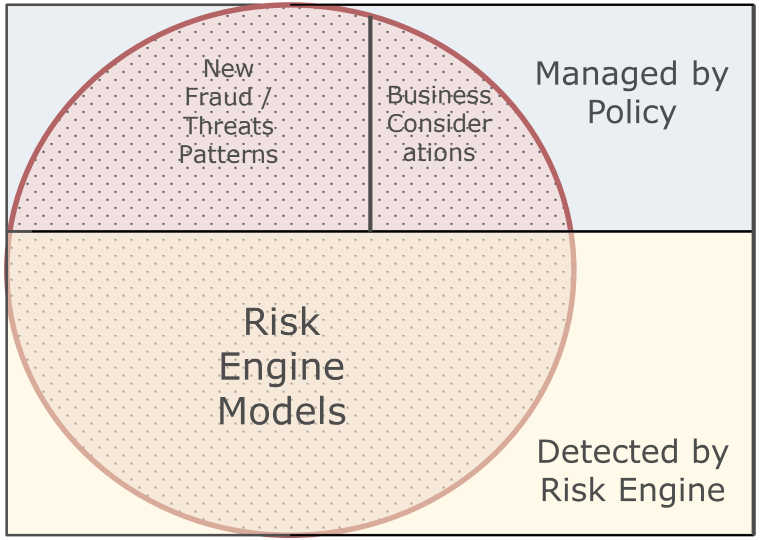
- **User cases:**
  - What customers like me have encountered
  - Recommend best known methods for protection

- **Example**
  - Recommending rules for policy of Web Fraud Detection management
  - Using user-user collaborative filtering
  - We will explore this in the next slides…



Fraud Detection Policy Overview

- **Credit card fraud detection engine**
  - Targeted to manage fraud events and business goals
  - Consists of:
    - Machine learning based risk engine
    - Policy i.e. set of rules



- What is a rule?

$$Rule = \{Conditions, Action, Meta\}$$

$$Condition = \{Sensor, Operation, Value\}$$

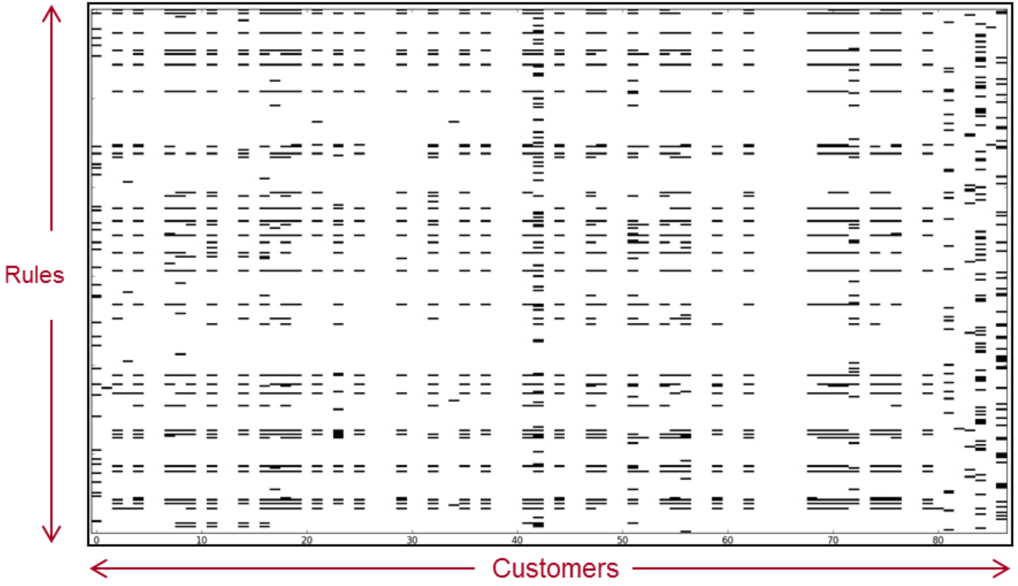
$$Action = Accept, Challenge, Block$$

$$Meta = \{Creation\ time, Fraud\ count, Fraud\ amount, False\ positive\ count\}$$

Rules Recommendation System

- **Constructing user-item (customer-rule) matrix**
  - Rules decomposition (logical or, lists)
  - Implicit rating calculation for each rule@customer
- **Similarity measure between customers**
  - Similar policy
  - Similar customers attributes
- **Find “good” rules**
  - Potentially good rating for a customer
- **Post processing**
  - Recommended rules clustering
- **Evaluation**

Visualization of customers – rules matrix



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Rules Collaborative Filtering

- **“Predict” rating of a rule for specific customer based on the ratings at other customers**
  - Weighted by similarity between customers
- **Preserve each customer policy preferences**
  - Avoid mean centering with average rule performance
- **Measure similarity between customers according to:**
  - How similar are their policies
  - How similar is their context
- **Selecting the rules with the highest rating**
  - Also passing a threshold that is specific to each customer

Predicted rating of rule i at user a

Rating of rule i at user u

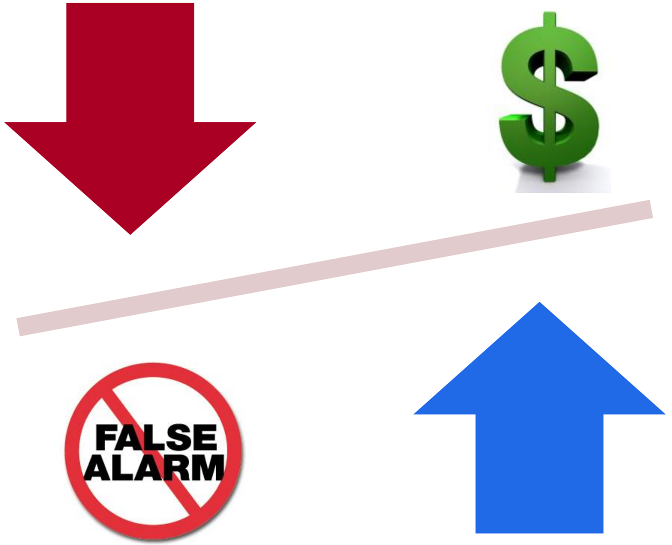
Similarity between user a and user u

$$P_{a,i} = \frac{\sum_{u=1}^{n} r_{u,i} * w_{a,u}}{\sum_{u=1}^{n} w_{a,u}}$$

$$w_{a,u} = \underbrace{\frac{0.5(\vec{R}_a * \vec{R}_u)}{\|\vec{R}_a\| * \|\vec{R}_u\|}}_{\text{Similarity between rule sets}} + \underbrace{\frac{0.5(\vec{M}_a * \vec{M}_u)}{\|\vec{M}_a\| * \|\vec{M}_u\|}}_{\text{Similarity between customers' meta (location, industry, size, …)}}$$

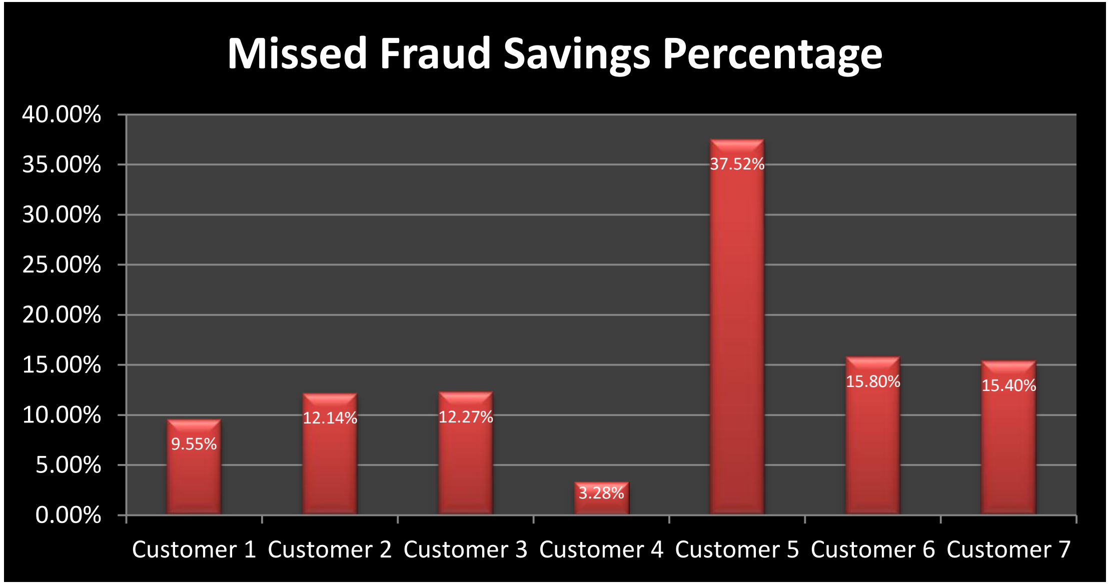
Evaluation

- **Metrics should be specific to application**
  - In this case fraud detection
- **Key performance indicators are:**
  - <u>Amount</u> of money savings due to missed fraud detection – the higher the better
  - <u>Count</u> of false alerts – the lower the better
- **Each customer has its own preferences**
  - $1000 may high amount for one customer and low amount for another
  - 10 false alerts may be too high for one customer and acceptable for another
- **In the end of the day, online evaluation protocol is needed to fine tune the model**



Rules Recommendation POC Results

- **Data**
  - 87 customers
  - 306 rules
  - 4 months transactions



- **Average increase in fraud savings: 15% (and up to 37%)**
  - Adding only 9 false alerts over the test period

Summary

- **Intelligence sharing is a key for fighting cyber attacks effectively**

- **Current intelligence sharing is very basic and manual; it is time for crowdsourcing and advanced analytics to step in**

- **Crowdsourcing can be leveraged in all levels of the security analyst work**
  - Prioritization
  - Investigation
  - Prediction / remediation

- **All these are enablers for high level co-operation that can keep the good guys one step ahead of the bad guys**

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Thank You

Email me: zohar.duchin@rsa.com