

Leveraging cybersecurity with machine-learning

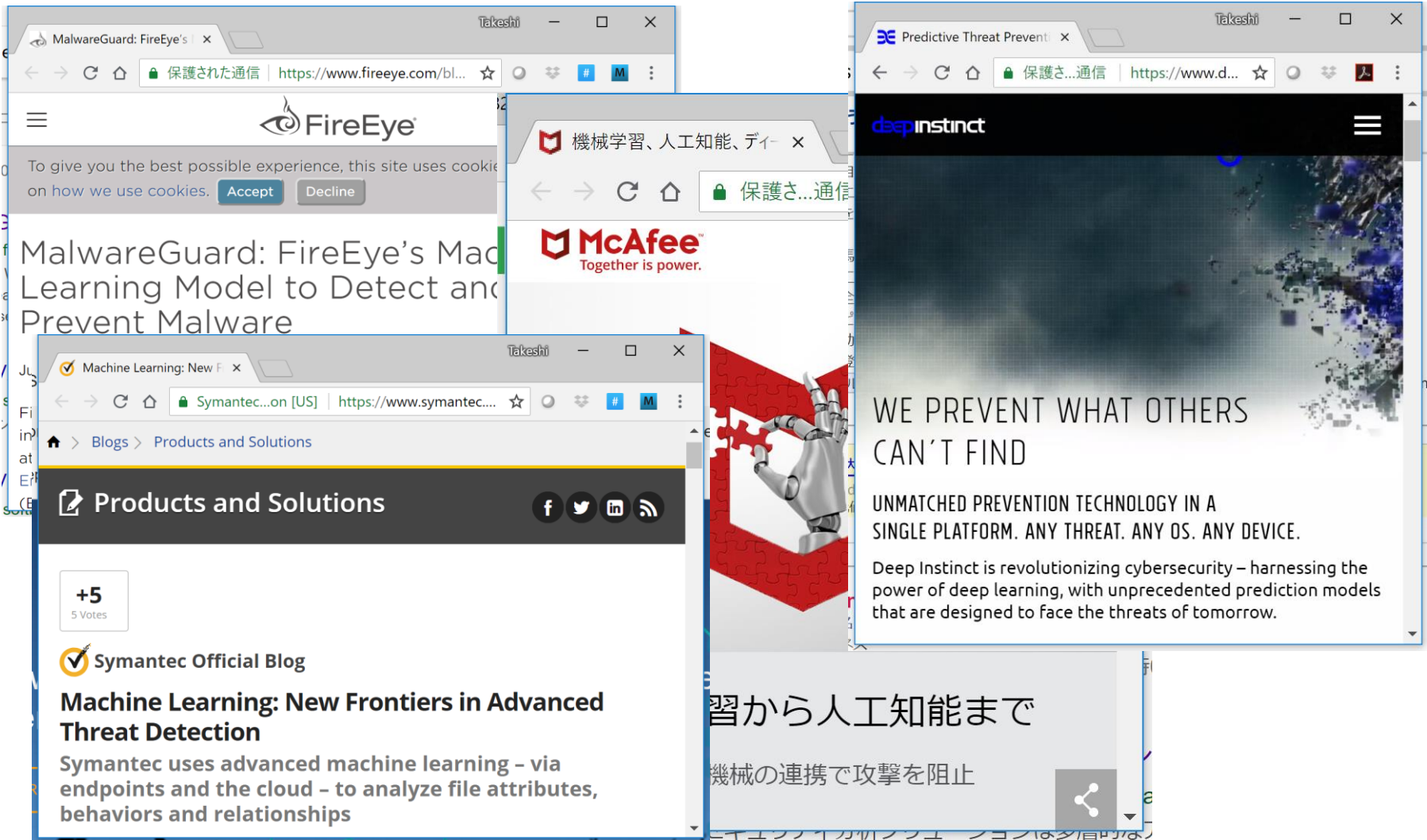
Takeshi Takahashi, Ph.D., CISSP, PMP

Research Manager

Cybersecurity Laboratory / AI Science R&D Promotion Center
NICT

1. The use of AI for cybersecurity in these days
2. Our research activities in a nutshell

AI techniques are said to be used in industries



MalwareGuard: FireEye's Machine Learning Model to Detect and Prevent Malware

機械学習、人工知能、データ

McAfee
Together is power.

Symantec Official Blog
Machine Learning: New Frontiers in Advanced Threat Detection
Symantec uses advanced machine learning - via endpoints and the cloud - to analyze file attributes, behaviors and relationships

deepinstinct

WE PREVENT WHAT OTHERS CAN'T FIND

UNMATCHED PREVENTION TECHNOLOGY IN A SINGLE PLATFORM. ANY THREAT. ANY OS. ANY DEVICE.

Deep Instinct is revolutionizing cybersecurity – harnessing the power of deep learning, with unprecedented prediction models that are designed to face the threats of tomorrow.

学習から人工知能まで

機械の連携で攻撃を阻止

Anti-virus vendors claim that they use deep learnings, but the algorithms or the specs they use were non-disclosed thus the details were unknown.³

The use of AI for cybersecurity is a hot topic now

Major research organizations work on the applicability of AI techniques for cybersecurity in these days. Here are the list of organizations that presented AI-related papers in USENIX Security 2018.

Europe

- EPFL
- Fraunhofer FKIE
- Max Planck Institute for Informatics
- RWTH Aachen University
- Siemens CERT
- Universidade de Lisboa

Israel

- Bar-Ilan University

Asia

- Chinese Academy of Science
- Beijing Jiaotong University

United States

- Boston University
- Columbia University
- Florida Institute of Technology
- Google Inc
- Indiana University
- Iowa State University
- MIT
- UC Santa Barbara
- University of Chicago
- University of Delaware
- University of Illinois
- University of Maryland
- Virginia Tech

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- Lancaster University
- University College London

Asia

- Inha University
- Peking University
- Zhejiang University
- The Hong Kong Polytechnic University
- Chinese Academy of Sciences
- Hanyang University
- National University of Singapore

United States

- University of Central Florida
- Florida International University
- Northwest University
- Lehigh University
- The Pennsylvania State University
- Virginia Tech
- University of Pennsylvania
- Symantec
- UC Riverside
- UC Berkeley
- University of Illinois at Urbana-Champaign
- University of Massachusetts

Traffic anomaly detection & malware detection (long standing area)

- Explainable system
- Performance improvements /real-time operations

Proactive defense techniques

- Program debloating (minimize vulnerabilities)
- Watermarking DNN
- Event prediction

Attacks on computing systems

- Solving captcha
- Malfunctioning voice recognition systems

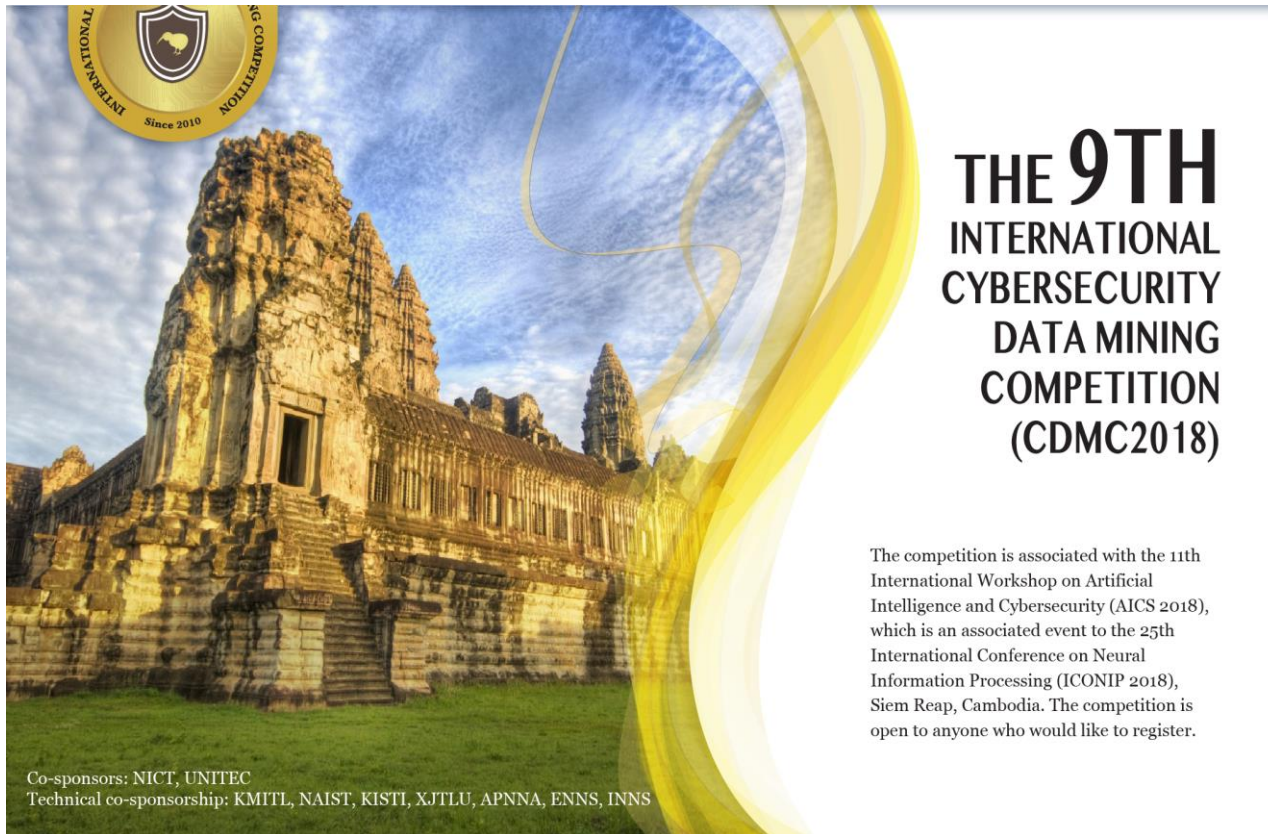
Deanomysation (attacks against privacy)

- Code Authorship Identification
- Document author attribute classification
- Identification of account pertaining review comments

Vulnerabilities of ML

- Poisoning attacks
- Vulnerabilities of transfer learning
- Attribute inference attacks
- Model reuse attack

We worked on AI x cybersec. for more than a decade 



**THE 9TH
INTERNATIONAL
CYBERSECURITY
DATA MINING
COMPETITION
(CDMC2018)**

The competition is associated with the 11th International Workshop on Artificial Intelligence and Cybersecurity (AICS 2018), which is an associated event to the 25th International Conference on Neural Information Processing (ICONIP 2018), Siem Reap, Cambodia. The competition is open to anyone who would like to register.

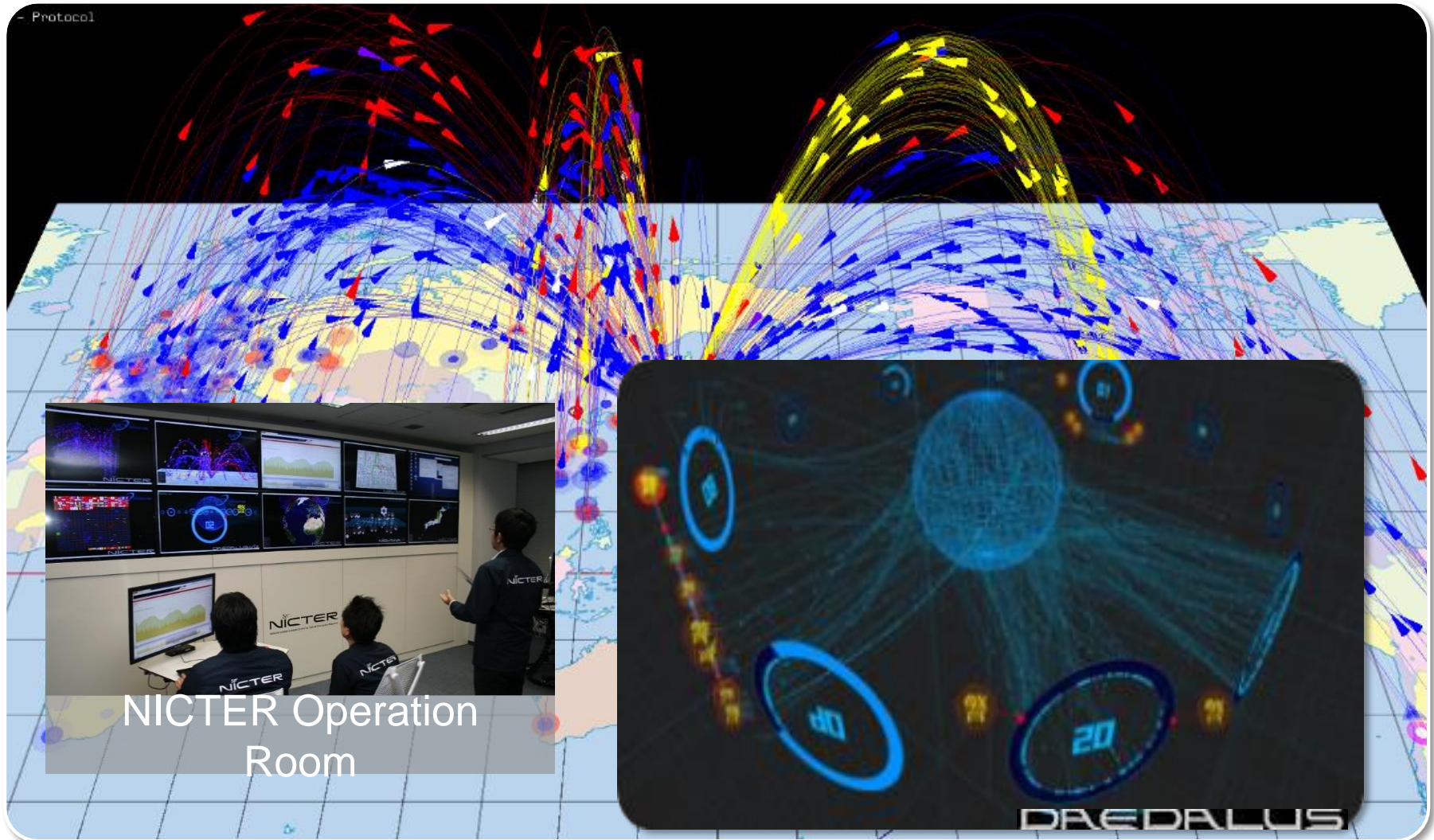
Co-sponsors: NICT, UNITEC
Technical co-sponsorship: KMITL, NAIST, KISTI, XJTTLU, APNNA, ENNS, INNS

- 11th International Data Mining and Cybersecurity Workshop (DMC), 2018
- 9th International Cybersecurity Data Mining Competition (CDMC), 2018

Our network monitoring systems accumulates data



- ✓ We monitor large-scale darknet spaces
- ✓ We built and have been operating systems, e.g., NICTER and DAEDALUS



NICTER Operation Room

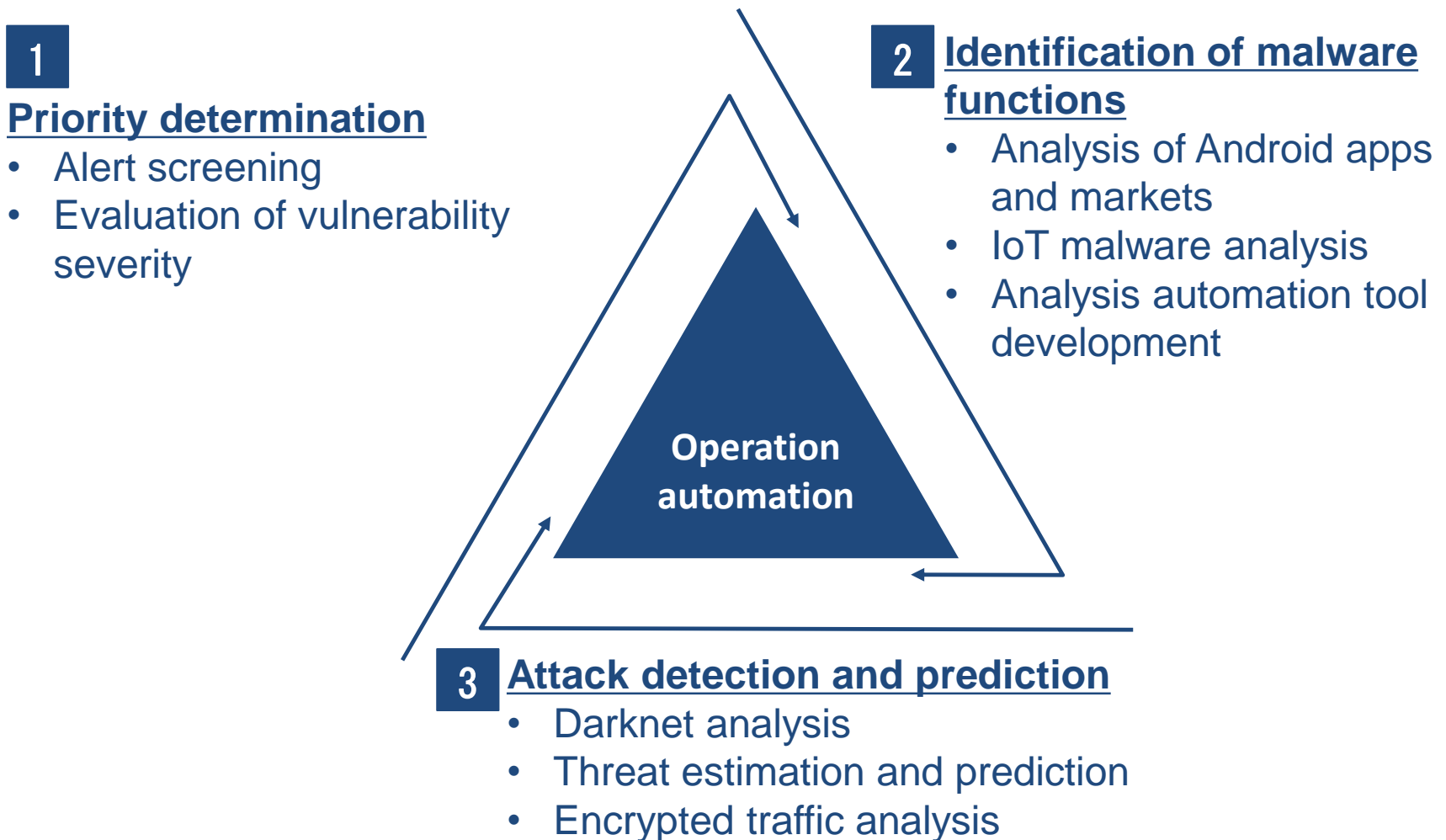
DAEDALUS

Our dataset



Category	Examples of accumulated data
Darknet related data	Data on the traffic sent to unused IP address spaces. This includes pcap files, statistical information, and malicious host information.
Livernet related data	Traffic data within NICT. This includes pcap files, flow data, security alerts generated by security appliances.
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Android related data	APK files and applications' metadata, e.g., category and description of applications
Blogs and articles	Tweets, security vendor blogs, etc.
Web crawler	URL list, Web contents, their evaluation results, etc.
Honeypot data	Data from High-interaction/low-interaction honey pots and high-interaction/low-interaction client honey pots
Commercial Intelligence data	Information on the sites hosting malware, bot, C&C server list, domain history, malware samples, threat reports, etc. purchased from VirusTotal, SecureWorks, Anubis, DomainTools, Malnet, Team 5, etc.

We conduct R&D on AI techniques that analyze and understand security situation and automate security operations within an organization.



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1

Priority determination

- Alert screening
- Evaluation of vulnerability severity

2

Identification of malware functions

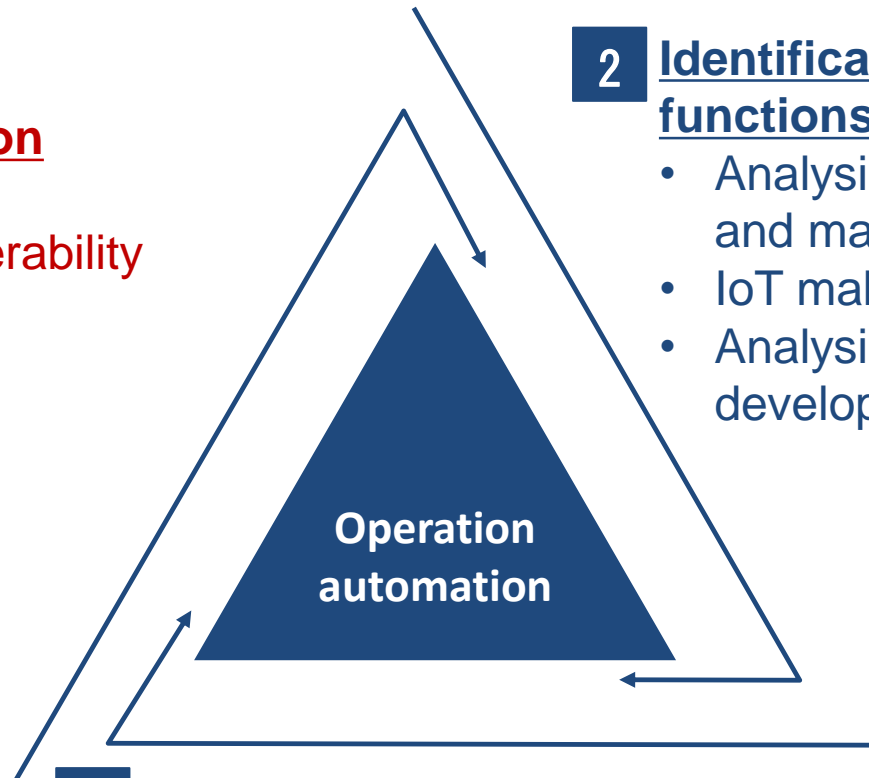
- Analysis of Android apps and markets
- IoT malware analysis
- Analysis automation tool development

Operation
automation

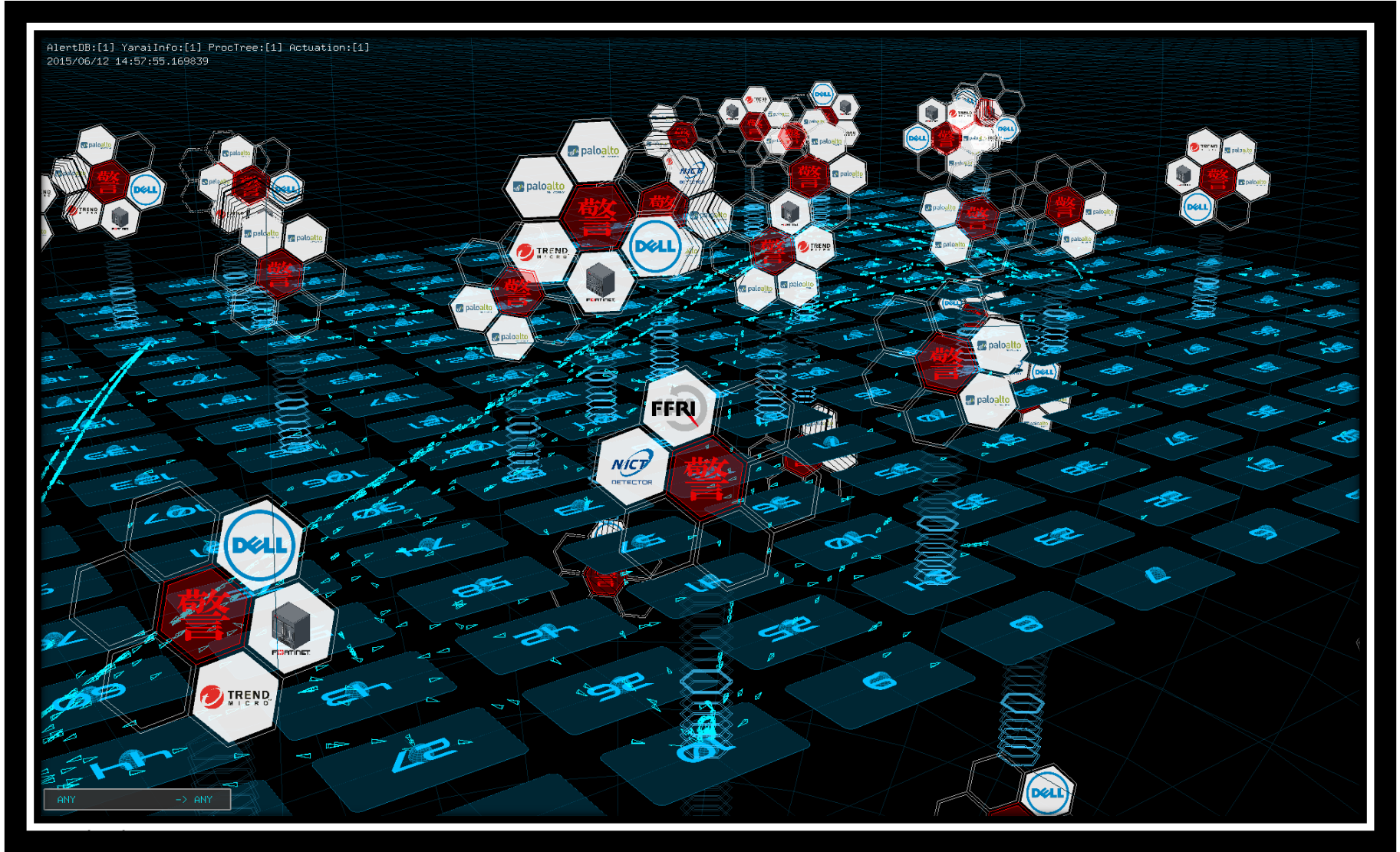
3

Attack detection and prediction

- Darknet analysis
- Threat estimation and prediction
- Encrypted traffic analysis

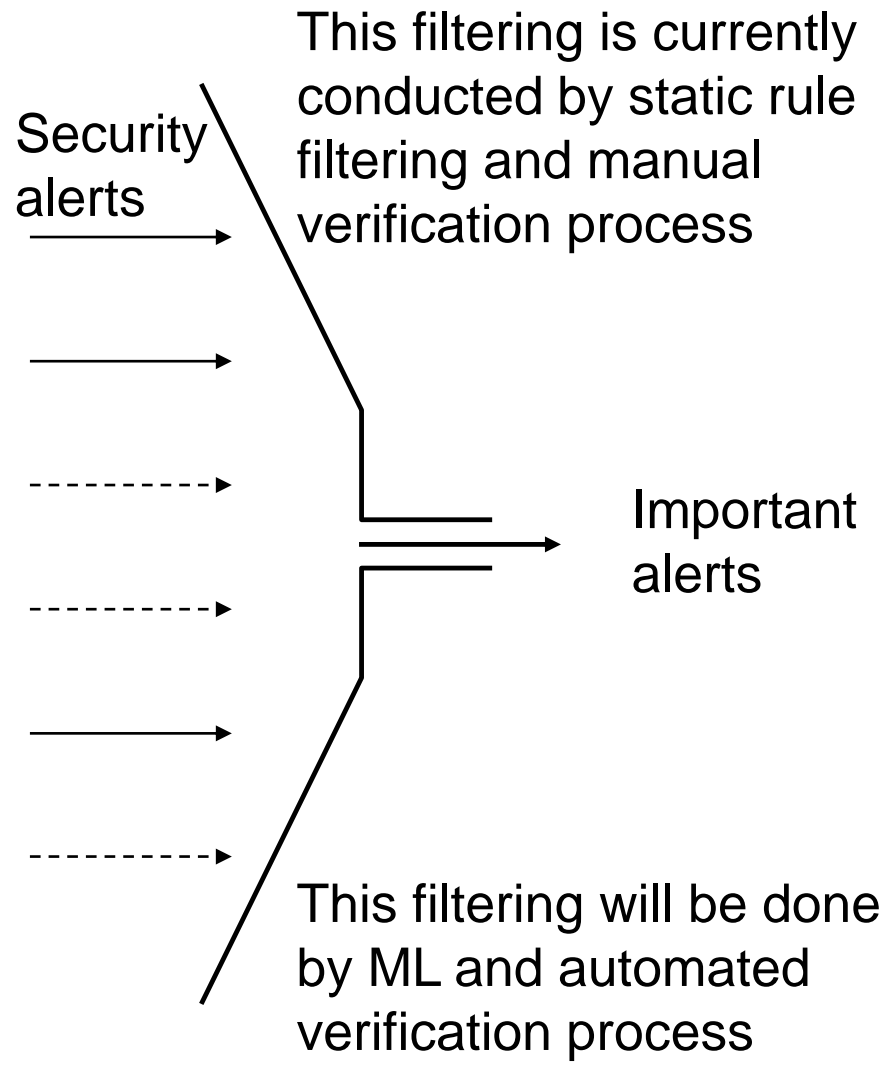


NIRVANA Kai integrates security appliances

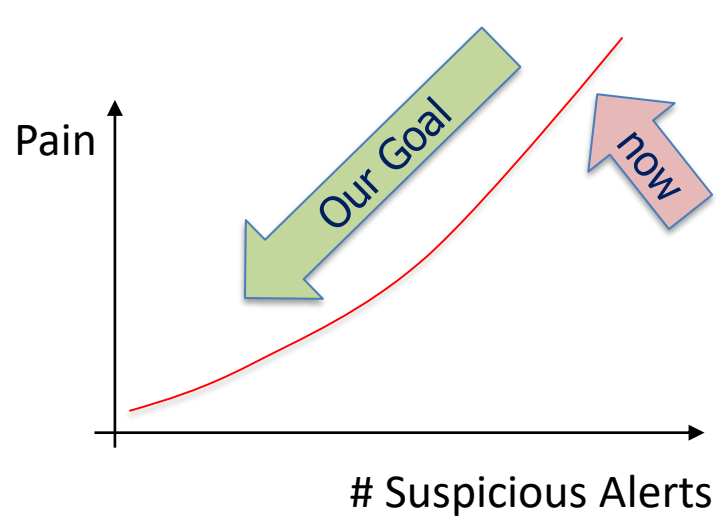


Alert screening and prioritization

Security appliances



Difficulties in our current security operations



One Expert
4 dedicated HOUR
Tedious Work

Our research focus



We conduct R&D on AI techniques that analyze and understand security situation and automate security operations within an organization.

1

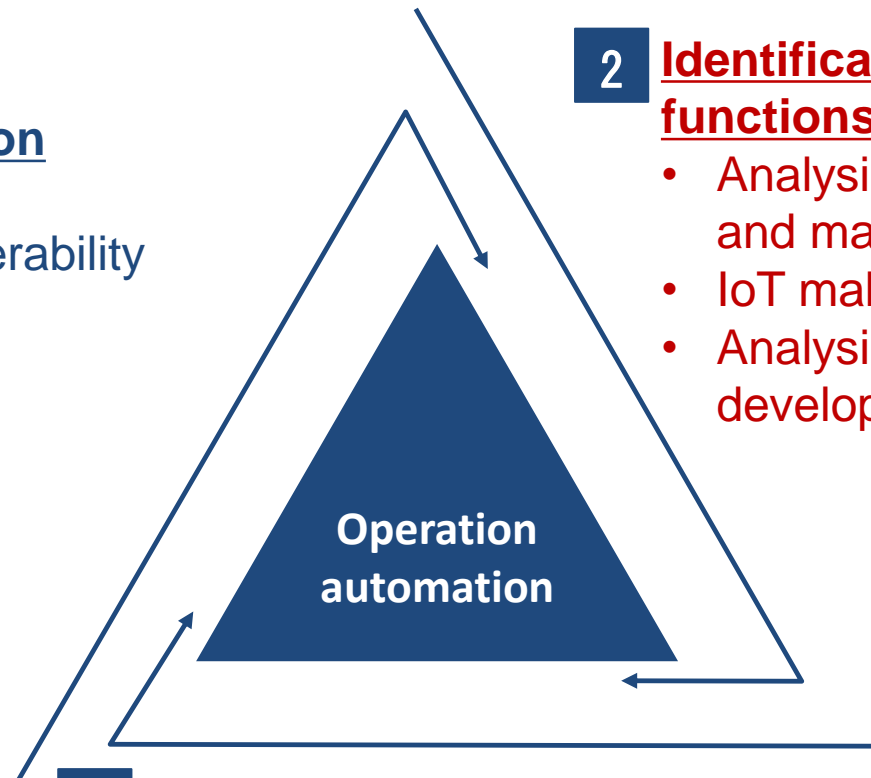
Priority determination

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2

Identification of malware functions

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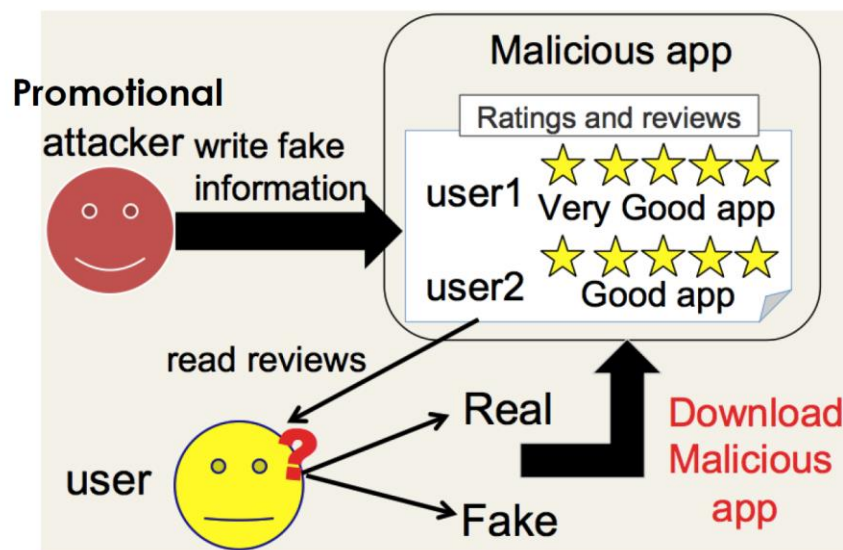


3

Attack detection and prediction

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1. Analyses on promotional attacks and demotional attacks on Android app markets



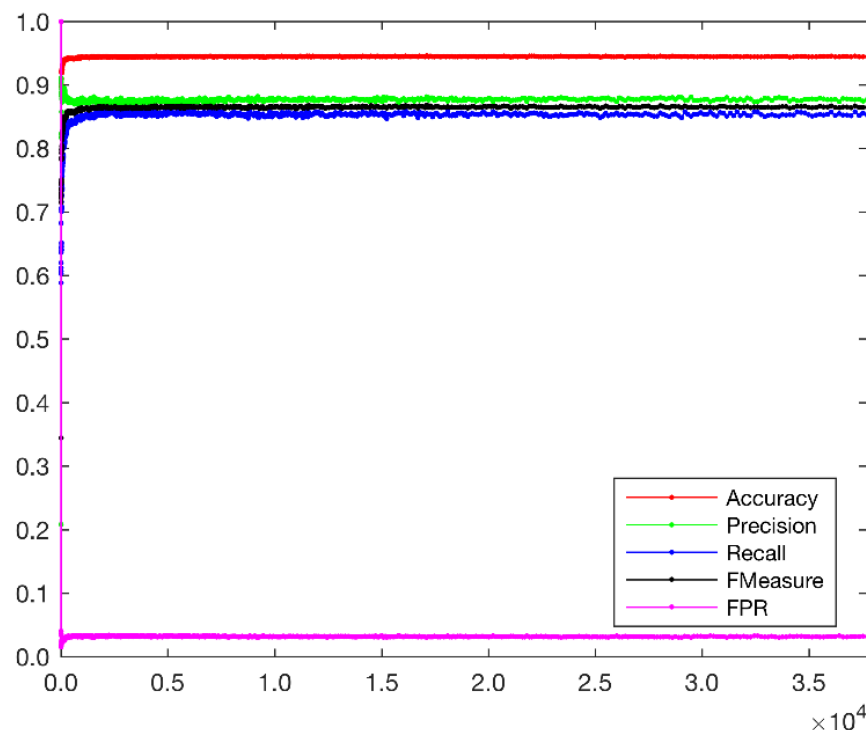
2. Android malware detection and classification

1. SVM/SVM-RFE approach using api calls, permission requests, category, and app descriptions.
2. Deep learning approach
3. Integration of static and dynamic analyses

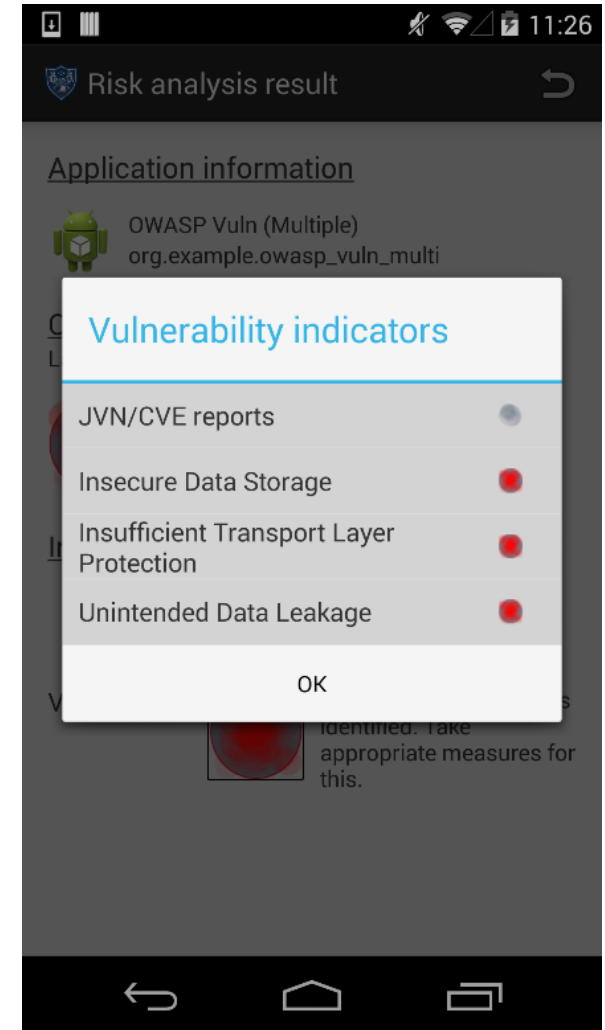
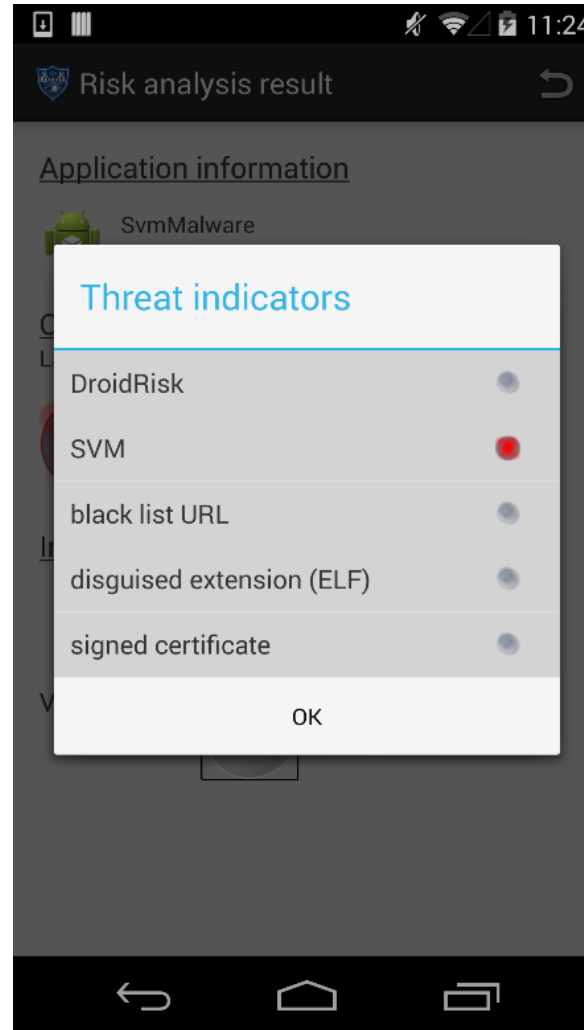
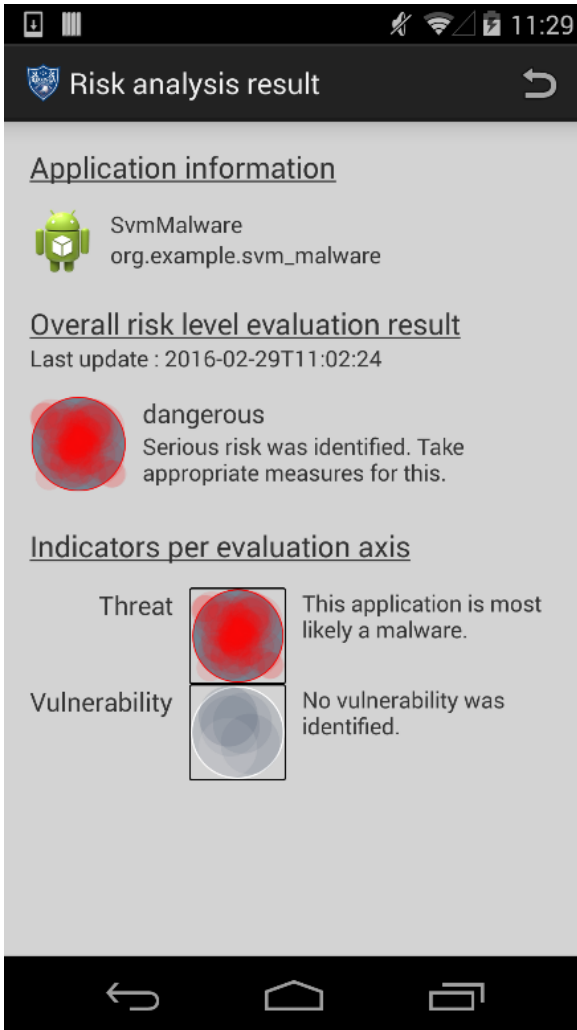
Feature selection improves the performance further



- We detect malware using SVM-RFE (Accuracy = 94.59 %)
 - Features: permission requests, API calls, app categories, clusters(generated from app descriptions)
 - 1,439 out of 30,000 features are used to produce the best performance
 - Influential features: API calls, some permission requests and application categories. (cluster feature barely contributes to the performance)
- We are currently evaluating the effectiveness of neural network techniques (Accuracy \doteq 99.79)

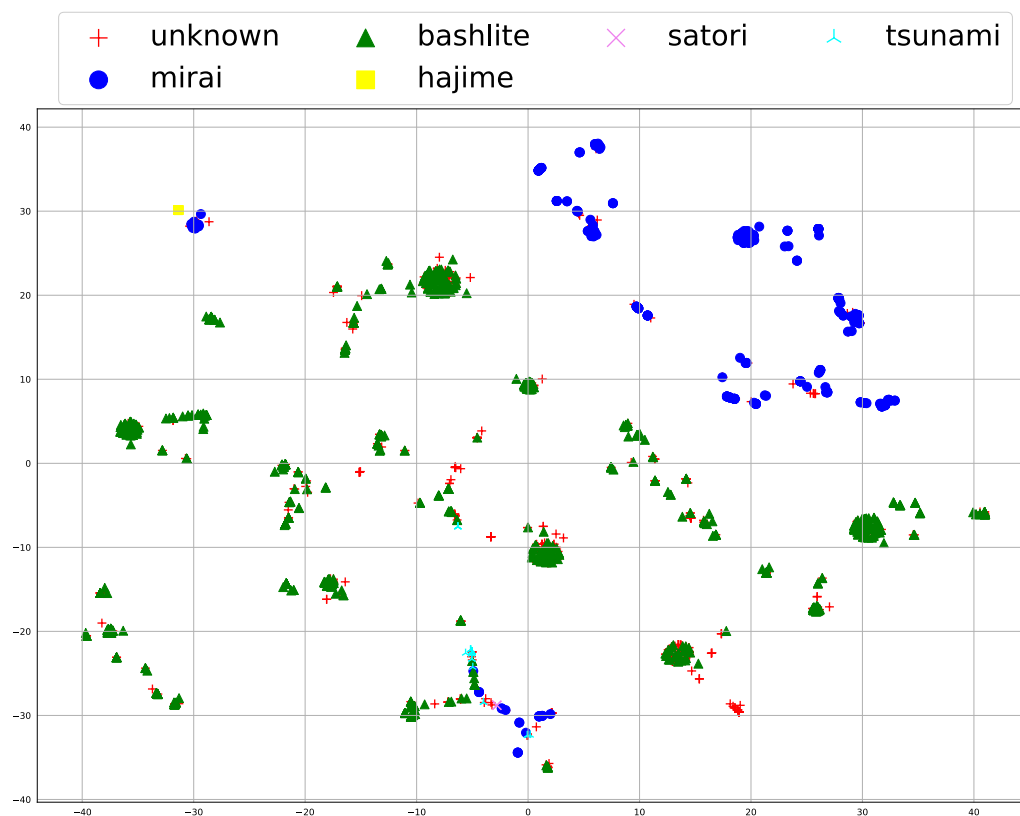
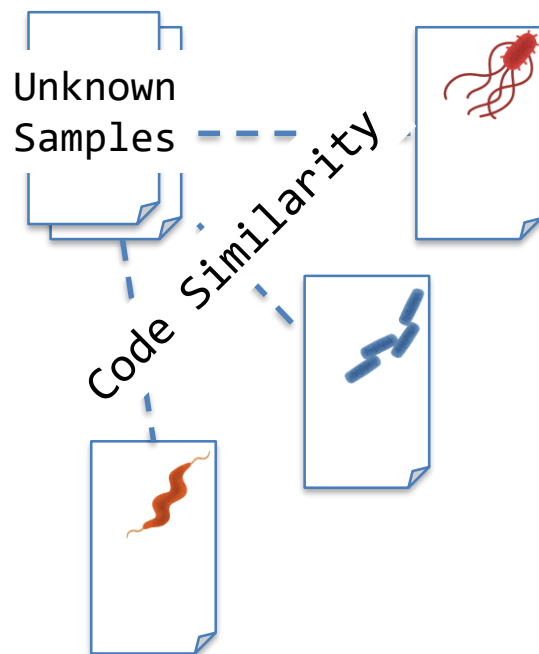


We identify Android malware and visualize that



Dataset used in the paper will be available soon at <http://mobilesec.nict.go.jp>.

We classified unknown samples into several malware families to catch a hint about efficient analysis of those samples.

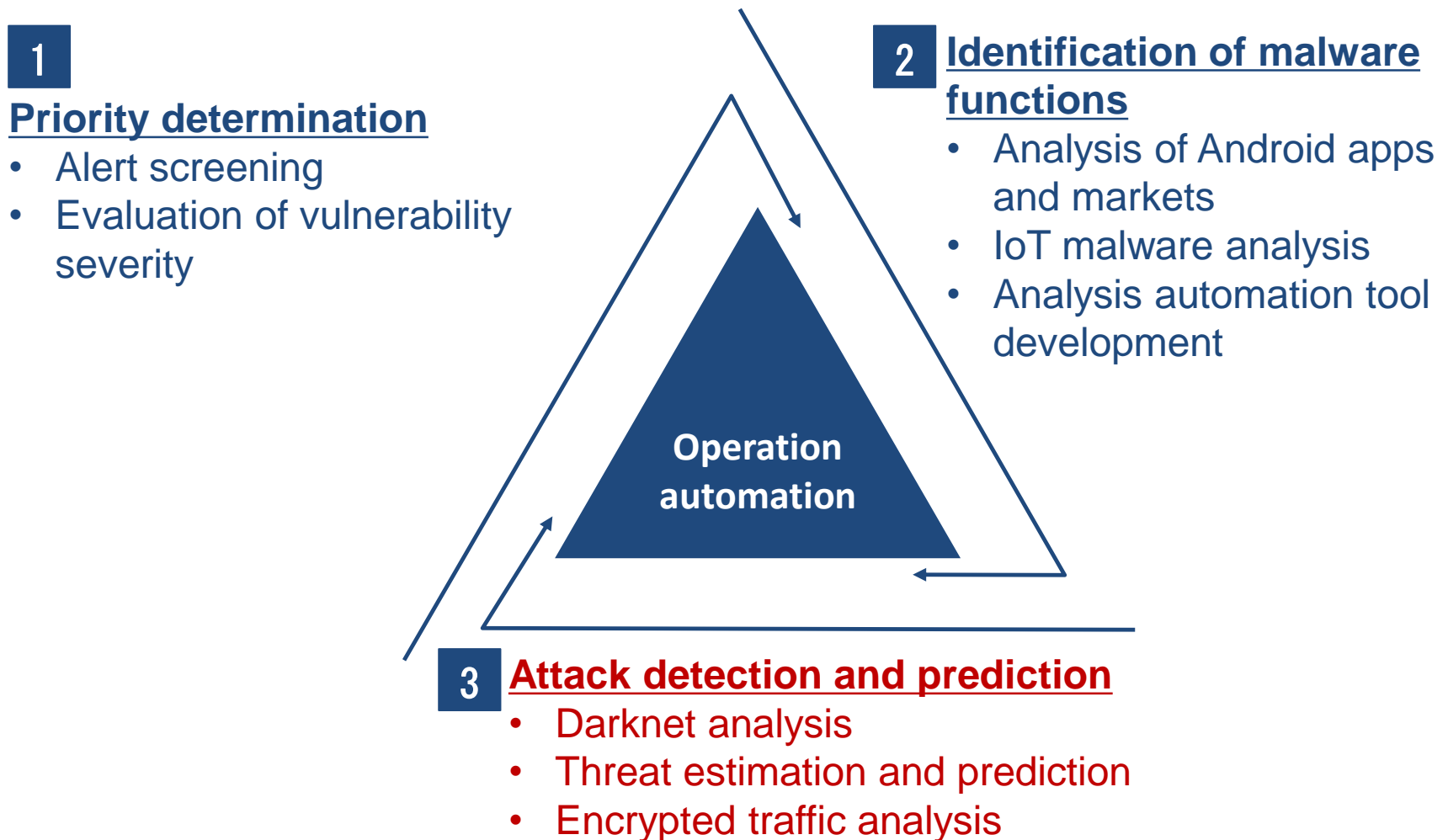


Samples mapped on a two-dimensional plane with T-SNE

Our research focus

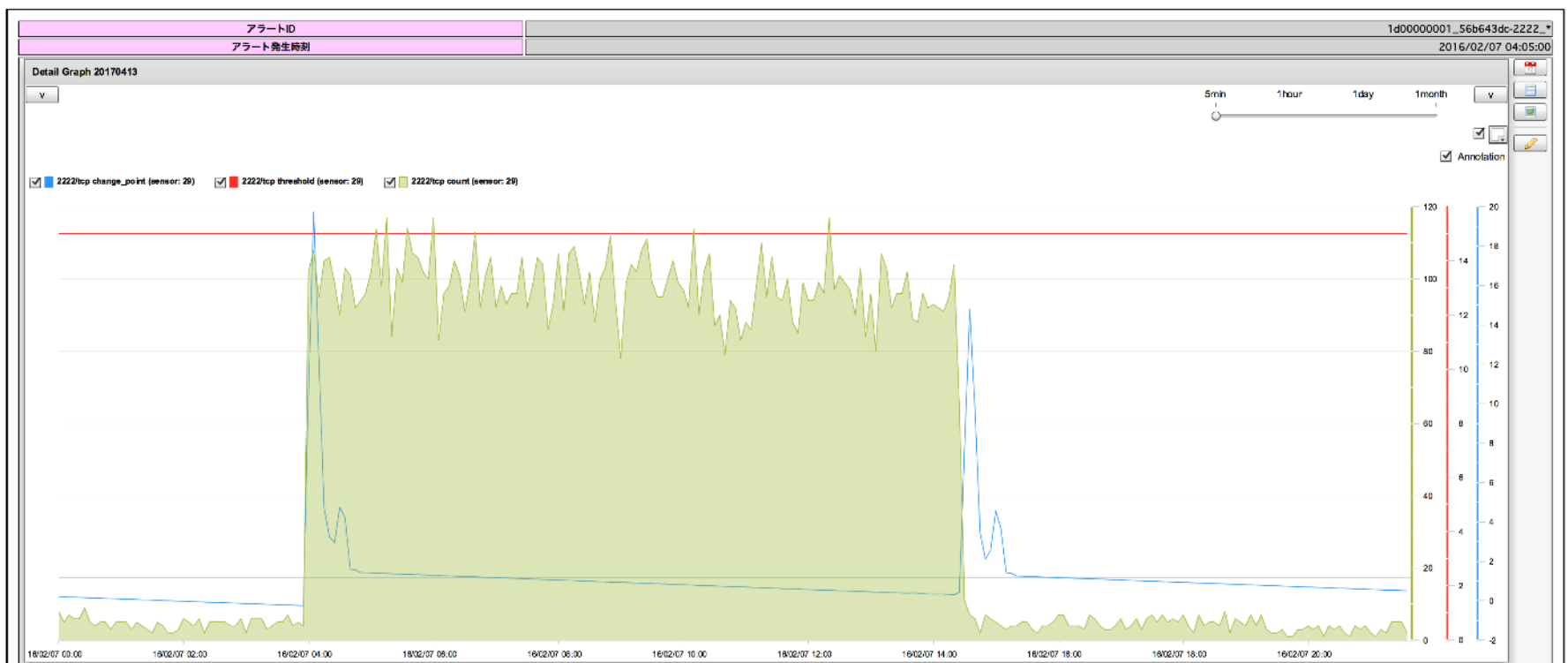


We conduct R&D on AI techniques that analyze and understand security situation and automate security operations within an organization.



We detect the coordinated actions/trend changes

Activities of botnet computers are often coordinated (initiated by C&C server). Thus the change of the coordinated actions can be viewed as the change of traffic trend change



In this figure, horizontal axis represents time while the vertical axis represents the number of packets sent to our darknet address space. This figure represents an example case of a malware being activated and stopped at certain time.

Alerts are generated upon detecting such points



Filter Conditions

Alert Time

<< 32227 32228 32229 32230 32231 32232 32233 32234 32235 32236 32237 32238 32239 32240 32241 >>

Number of Display Cur: 644661-644680 / All: 645089

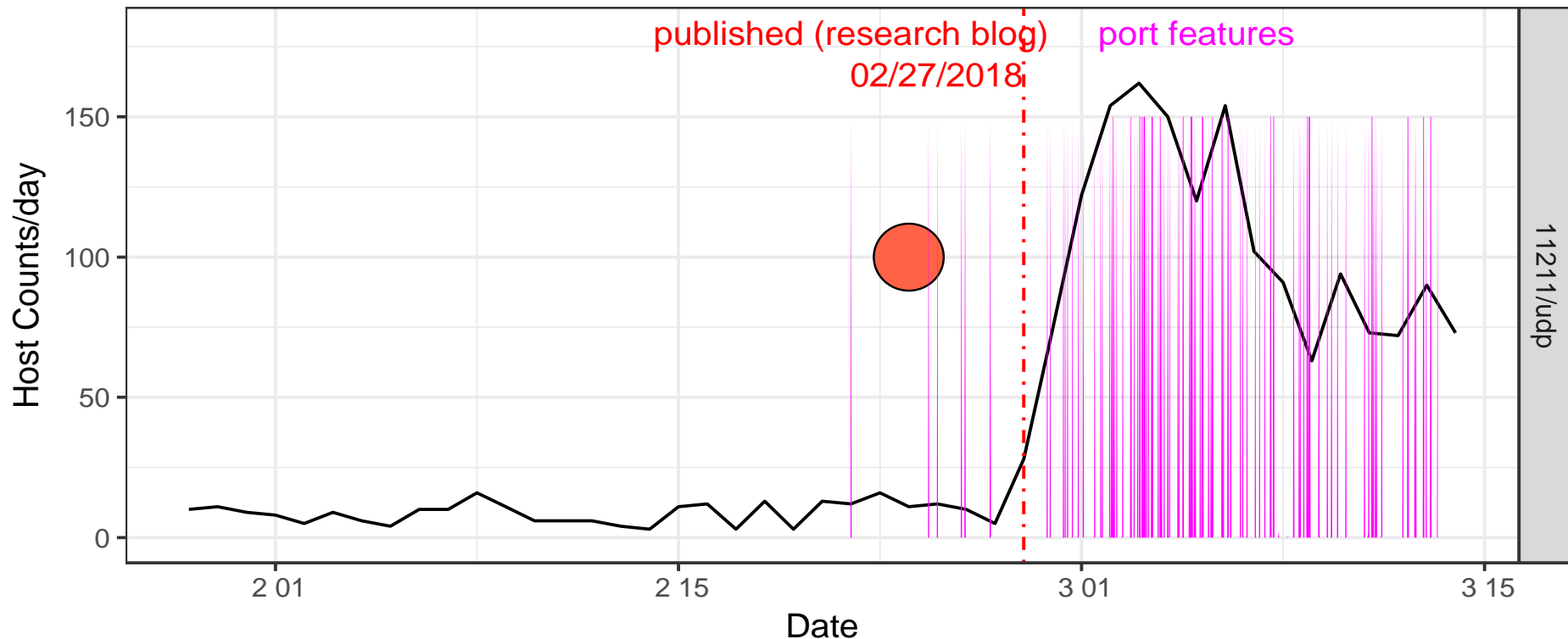
No.	Alert Time	Sensor ID	Type	Period	Target	Option	Change Point Score	Threshold	Cause Target	Cause Option	Cause Count	Detail Info
<input type="checkbox"/> 644661	2016/02/07 08:40:01	29	tpd00is	5m	0-1024	*	22.100443	15	139	*	1	detail
<input type="checkbox"/> 644662	2016/02/07 08:10:03	29	tpd00is	5m	1025-4999	*	19.837684	15	3306	*	2	detail
<input type="checkbox"/> 644663	2016/02/07 08:10:02	29	tpd00is	5m	0-1024	*	16.937063	15	22	*	22	detail
<input type="checkbox"/> 644664	2016/02/07 06:40:02	29	tpd00is	5m	0-1024	*	22.100847	15	102	*	3	detail
<input type="checkbox"/> 644665	2016/02/07 05:40:01	29	tpd00is	5m	0-1024	*	16.967217	15	143	*	5	detail
<input type="checkbox"/> 644666	2016/02/07 05:10:03	29	tpd00is	5m	10000-14999	*	19.401623	15	10000	*	10	detail
<input type="checkbox"/> 644667	2016/02/07 04:40:02	29	tpd00is	5m	1025-4999	*	19.725899	15	2222	*	108	detail
<input type="checkbox"/> 644668	2016/02/07 04:40:02	29	tpd00is	5m	5000-9999	*	19.676857	15	8000	*	99	detail
<input type="checkbox"/> 644669	2016/02/07 04:40:01	29	tpd00is	5m	0-1024	*	22.842586	15	502	*	22	detail
<input type="checkbox"/> 644670	2016/02/07 04:10:01	29	tpd00is	5m	0-1024	*	18.446741	15	80	*	26	detail
<input type="checkbox"/> 644671	2016/02/07 04:10:02	29	tpd00is	5m	5000-9999	*	22.09943	15	7071	*	7	detail
<input type="checkbox"/> 644672	2016/02/06 22:30:01	29	tpd00is	5m	0-1024	*	20.370078	15	82	*	5	detail
<input type="checkbox"/> 644673	2016/02/06 22:30:17	29	upd00is	5m	0-1024	*	16.89279	15	53	*	5	detail
<input type="checkbox"/> 644674	2016/02/06 22:30:18	29	upd00is	5m	53	*	16.892791	15	53	*	5	detail
<input type="checkbox"/> 644675	2016/02/06 22:00:02	29	tpd00is	5m	0-1024	*	16.683782	15	22	*	109	detail
<input type="checkbox"/> 644676	2016/02/06 22:00:17	29	tpd00is	5m	22	*	17.493689	15	22	*	109	detail
<input type="checkbox"/> 644677	2016/02/06 21:30:14	29	upd00is	5m	0-1024	*	22.100837	15	161	*	4	detail
<input type="checkbox"/> 644678	2016/02/06 21:30:16	29	upd00is	5m	161	*	22.100445	15	161	*	4	detail
<input type="checkbox"/> 644679	2016/02/06 21:00:02	29	tpd00is	5m	0-1024	*	16.178003	15	91	*	1	detail
<input type="checkbox"/> 644680	2016/02/06 19:10:02	29	upd00is	5m	5000-9999	*	22.100443	15	5006	*	6	detail

All Select/Unselect

<< 32227 32228 32229 32230 32231 32232 32233 32234 32235 32236 32237 32238 32239 32240 32241 >>

1. Our prototype works, but it needs to work in real-time, and it needs to minimize false positives/negatives.
2. We are currently approaching this issue with glasso, NMF, and tensor decomposition techniques, respectively.

Real-time botnet detection using tensor decomposition



1. We were able to identify the coordinated action prior to the issue is published by a well-known research blog
2. We were able to identify the coordinated action before NICTER system identifies trend change

1. H.Kanehara, Y.Murakami, J.Shimamura, T.Takahashi, D.Inoue, N.Murata, "Real-Time Botnet Detection Using Nonnegative Tucker Decomposition," ACM SAC, 2019.
2. B.Sun, T.Ban, S.Chang, Y.Sun, T.Takahashi, D.Inoue, "A Scalable and Accurate Feature Representation Method for Identifying Malicious Mobile Applications," ACM SAC, 2019.
3. T.Takahashi, T.Ban, "Android Application Analysis using Machine Learning Techniques," Intelligent Systems Reference Library, 181 - 205, 2019.
4. S.Chang, Y.Sun, W.Chuang, M.Chen, B.Sun, T.Takahashi, "ANTSdroid:Using RasMMA Algorithm to Generate Malware Behavior Characteristics of Android Malware Family," IEEE PRDC, 2018.
5. L.Zhu, T.Ban, T.Takahashi, D.Inoue, "Employ Decision Value for Binary Soft Classifier Evaluation with Crispy Reference," ICONIP, 2018.
6. R.Iijima, S.Minami, Z.Yunao, T.Takehisa, T.Takahashi, Y.Oikawa, T.Mori, "Poster: Audio Hotspot Attack: An Attack on Voice Assistance Systems Using Directional Sound Beams," ACM CCS, 2018.
7. T.Takahashi, B.Panta, Y.Kadobayashi, K.Nakao, "Web of cybersecurity: Linking, locating, and discovering structured cybersecurity information," Int J Commun Syst. 2017.

Our dataset, a vehicle for research collaborations



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