Al-Driven Cyber Security

Frofessor Yang Xiang ital Research & Innovation Capability Platform Swinburne University of Technology Email: yxiang@swin.edu.au



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Research on Cyber Security @ Swinburne

- A team of world leading capabilities in cyber security
- We develop innovative technologies for securing cyberspace
- We work with industry and government to provide protection from major cyber security threats





Core Capabilities @ Swinburne



Cutting Edge Facilities

• Dedicated Equipment



• Huge Amount of Data





How Al models learn and understand what is normal and what is abnormal?



Real+ritorId Data Modelling + Reasoning



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Research Methodology





Use Cases

Al-Driven Cyber Security

Deep vulnerable code analysis

ML based malware detection

Insider attack prediction

Adversarial machine learning Security incident prediction

Intelligent network monitoring

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Project – Ransomware Detection

- A ransomware attack can encrypt critical data, causing huge damages
- Our research
 - Ransomware life cycle
 - Software similarity and classification
 - Propagation modelling
 - Intelligent detection
 - Global sensors

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Cyber expert warns against supporting criminal syndicates amid global hacking

By Katri Llibu, wires

Updated 13 May 2017, 4:14pm

Companies affected by global ransomware attacks should not pay the ransom so as not to feed into the growing business of organised cyber crime, a security expert warns.

Attackers have used encryption algo files, which owners cannot access ur a ransom

Over 57,000 infections in 99 countrie

top targets, security software maker

The attacks have led to hospitals and



Traffic cameras in Victoria infected by WannaCry ransomware

detected, with Russia, Ukraine and 1 State government says 55 cameras were affected after a contractor introduced the virus to the system by mistake



O Speed cameras affected by the problem will be fixed in the 'next couple of days'. Photograph: Alan Porritt, IAAP





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Project – Insider Attack Detection

- Insider attacks are highlighted as "the most damaging risk"
- We design a novel fine-grained anomaly behaviour identification system to predict cyber insider attacks
- It can analyse big behaviour data, making real-time decision, and learning varying behaviour features,
- It can provide maximised protection to large-scale private networks









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Project – Deep Learning for Cyber

- Deep Learning techniques to discover vulnerabilities in source and/or binary code bases
 - Deep source analysis: New approaches, classification with representation learning and deep learning with multiple sources for code analysis
 - Deep binary analysis: Innovatively convert binary code to different data presentation such as image, and employ deep neural networks to assist binary analysis





Project – Adversarial Machine Learning for Cyber

- Advance the unexplored territory of adversarial machine learning defences, with focus on network security
 - Randomised projection reducing the curse of dimensionality that benefits attackers
 - Game theoretic formulations that seek limit points of cat-and-mouse attack and defence





Project – Classifying Internet Traffic for Security Applications

- Develop a set of novel techniques for Internet traffic classification, which is important to defend against the serious cyber-attacks and effectively minimise the damage
 - Real-time
 - Scalable
 - Robust
 - Private







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Detecting Software Vulnerabilities



Significance

Software vulnerabilities can critically:

- undermine the security of computer systems
- endanger the IT infrastructure of organizations





Intel Chip Vulnerabilities





High-impact Vulnerabilities

"Heartbleed" in OpenSSL library







High-impact Vulnerabilities

"Heartbleed" in OpenSSL library



Accounted for almost **66%** of active websites on the Internet.



Spreading of WannaCry





A Realistic Example – Heartbleed Vulnerability



The "Heartbleed" vulnerability in OpenSSL

A Realistic Example – Heartbleed Vulnerability



The integer *payload* is defined by the macro *n2s* that reads a sixteen bit integer from a network stream.

Hence, there is a need to inspect:

1) How information propagates from one statement to another

2) How the information flow is controlled by conditions

Fig. 1: The "Heartbleed" vulnerability in OpenSSL.

Challenges

1. The growing complexity of software



Challenges

2. Vulnerabilities are plenty

• Over 15,000 vulnerabilities reported in 2016 (over 280/week)





Challenges

- 3. Vulnerabilities are difficult to detect
 - Tedious and time-consuming
 - Sufficient understandings of projects and knowledge of security required
 - Security considerations are not prioritized and well-recognized



Scope





Machine Learning's Perspective





How do we convert **vulnerable code** to **effective features**?

Source code





Features that are:

- Representative
- Invariant

Classifiers

Distinctive

How do we convert **vulnerable code** to **effective features**?

Binary

9A D3 AF 03 67 69 91 3D 24 88 ...JJ.O....gi.=\$. ..[...r.Co_.... 72 01 43 6F 5F DC 9F 17 17 A0 ..'.CE....>il!. .<.`Z8.. 27 7B 17 FF B7 C1 98 61 7D E0 ..W.L'{....a}..S=.1...."hw. W.iZp....2 ...2%. 37 A2 B9 F5 85 98 D9 65 }X...m.7....e. Y....A.>Y.&S...r .Z.....D.....U(. 9F F8 6E DE ØB W/t...Ts...n...(6. =10...F....?.<.~..)#...dx>....>.. EB 84 99 CF D2 71 A2 27 41 73 0C 71 74 ...k....q.'As.qt 59 DB A8 28 1B 3F D6 21 10 6A 68 4C 2A 05 9 Y..(.?.!.jhL*.



• Distinctive



How do we convert **vulnerable code** to **effective features**?

Binary



How do we convert **vulnerable code** to **effective features**?



TECHNOLOGY

How to convert **vulnerable code** to **effective features**?





How to convert vulnerable code to effective features?



TECHNOLOGY

How to convert vulnerable code to effective features?



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How to convert **vulnerable code** to **effective features**?

Blank Lines of Code Source code Lines of Code /* ssl/d1_both.c */ Lines with Comments // [...] int dtls1 process heartbeat (SSL *s) Statements unsigned char *p = &s->s3->rrec.data[0], *pl; Physical Lines of Code unsigned short hbtype; unsigned int payload; Declarative Lines of Code unsigned int padding = 16; /* Use minimum padding */ Count /* Read type and payload length first */ Executable Lines of Code hbtype = *p++;Metrics n2s(p, payload); Code Lines with Comments if (1 + 2 + payload + 16 > s -> s3 -> rrec.length)return 0; /* silently discard per RFC 6520 sec.4*/ 13 Inactive Lines pl = p;14 // [...] 15 **Properties** Preprocessor Lines if (hbtype == TLS1_HB_REQUEST) { 16 unsigned char *buffer, *bp; 17 FanIn [11] int r: // [...] FanOut [11] buffer = OPENSSL_malloc(1 + 2 + payload + padding); bp = buffer; /* Enter response type, length and copy payload */ Path 22 *bp++ = TLS1 HB RESPONSE; 23 Cyclomatic Complexity (CC) [14 s2n(payload, bp); 24 memcpy(bp, pl, payload); 25 Modified CC [14] bp += payload; 26 /* Random padding */ 27 Complexity Strict CC [14] RAND_pseudo_bytes(bp, padding); 28 r = dtls1_write_bytes(s, TLS1_RT_HEARTBEAT, buffer, 29 Metrics Essential Complexity [14] 3 + payload + padding); 30 // [...] 31 Knots [36] if (r < 0) return r; 32 33 Nesting [10] // [...] 34 35 return 0;

36

How to convert vulnerable code to effective features?





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Machine Learning Algorithms









Research Trends



Our work

- Vulnerability Discovery with Function Representation Learning from Unlabeled Projects (accepted by CCS2017 Poster)
 - ✓ Function-level detection
 - ✓ Cross-project scenario
 - ✓ Representation learning with deep learning approach









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Key Assumptions

1. Vulnerable programming patterns are associated with many vulnerabilities, and these patterns can be revealed by analysing the program's ASTs



Research Question

1. How do we covert ASTs to vectors acceptable by ML algorithms while preserving the **structural** information?





[foo, int, params, param, int, x, stmnts, decl, int, y, op, =, call, bar, arg, x, for, int, i, ... return , y]

Key Assumptions

2. The sequence of elements in the textual vectors **resembles** sequences of words in natural language.

[foo, int, params, param, int, x, stmnts, decl, int, y, op, =, call, bar, arg, x, for, int, i, ... return , y]

Natural language: sentence.

AST: textual vector

[Hi, everyone, my, name, is, Guanjun, Lin, I, am, from, China, ..., I, can, speak, fluent, Chinese ,thanks]



Research Question

2. How do we covert ASTs to vectors acceptable by ML algorithms while preserving the **syntactic & semantic** information?





Word2vec Embeddings





Network Design





Our Work

1. Overcome the difficulty of obtaining manual labels by leveraging well-understood complexity metrics (used as a **proxy** as the substitute of data labels)



Our Work

2. Overcome the insufficiency of vulnerable data of the inactive open source projects by leveraging transfer-learned representations.



Our Work

2. Overcome the insufficiency of vulnerable data of the inactive open source projects by leveraging transfer-learned representations.



Results





Efforts Saved

Human efforts saved for manually

auditing potentially vulnerable

functions with our method.





Thank You – Q&A

