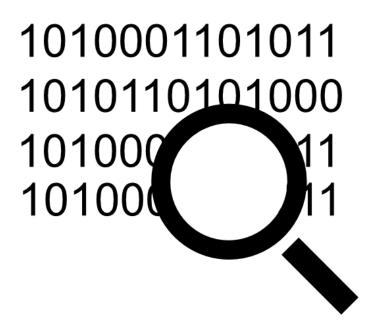
Binary analysis: Code Search

Yue Duan

Outline

- Code Search basics
- Research papers:
 - Scalable Graph-based Bug Search for Firmware Images
 - Neural Network-based Graph Embedding for Cross-Platform Binary Code Similarity Detection
 - DeepBinDiff: Learning Program-Wide Code Representations for Binary Diffing



Problem definition

- given two pieces of binary code (e.g., binary functions)
 - maybe in different architectures
 - maybe by different compilation configs
 - compilers
 - compiler versions
 - optimization levels
 - other options
 - o check if they are semantically equivalent or similar

Security applications

plagiarism detection

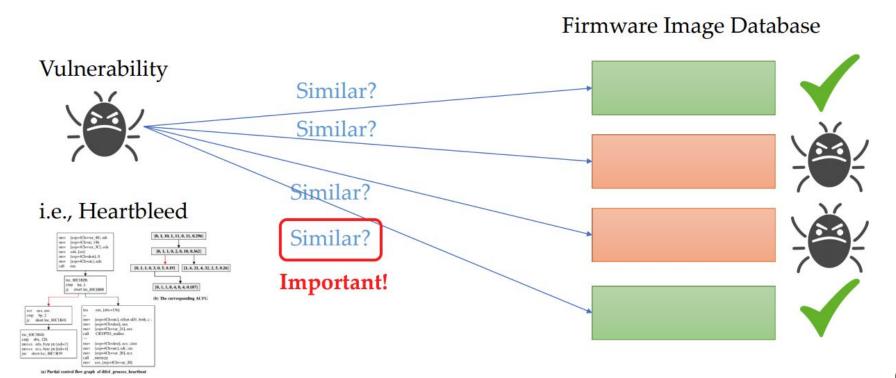
```
01 static void
                                                                   01 static void
   make blank (struct line *blank, int count)
                                                                   02 fill content (int num, struct line* fill)
03
     int i;
                                                                        (*fill).store.size = fill->store.length = num + 1;
      unsigned char *buffer;
                                                                        struct field *tabs;
      struct field *fields;
                                                                        (*fill).fields = tabs = (struct field *)
                                                                                   xmalloc (sizeof (struct field) * num);
     blank->nfields = count;
                                                                        (*fill).store.buffer = (char*) xmalloc (fill->store.size);
     blank->buf. size = blank->buf. length = count + 1;
                                                                   08. (*fill) .ntabs = num;
                                                                        unsigned char *pb;
     blank->buf.buffer = (char*) xmalloc (blank->buf.size);
     buffer = (unsigned char *) blank->buf.buffer;
                                                                        pb = (unsigned char *) (*fill).store.buffer;
     blank->fields = fields =
       (struct field *) xmalloc (sizeof (struct field) * count);
                                                                        int idx = 0;
                                                                        while (ick < num) { // fill in the storage
      for (i = 0; i < count; i++) {
13
                                                                          for (int j = 0; j < idx; j++)
14
15 }
                                                                          idx++;
                                                                   18 }
                   Original Code
                                                                           Plagiarized Code
```

Security applications

- vulnerability analysis
 - o i.e., vulnerability search in IoT

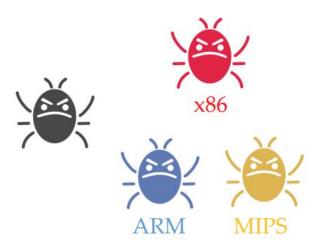


Vulnerability analysis



Challenges

Cross-Platform

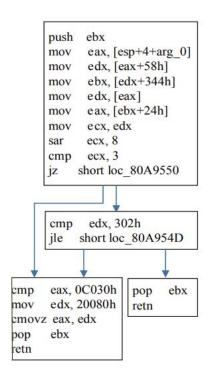


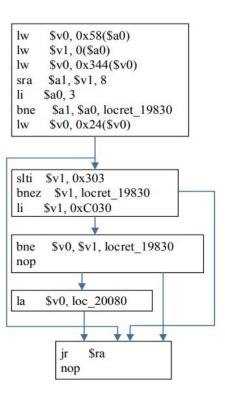
Scalability





Example



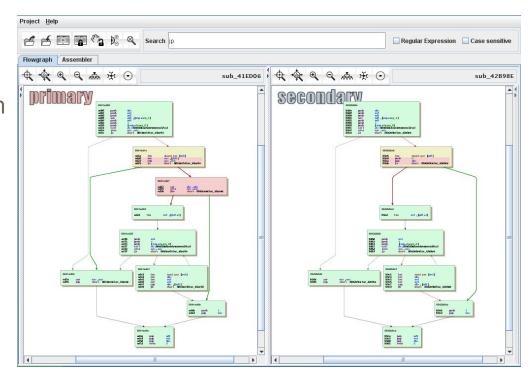


a) x86 assembly

b) MIPS assembly

Existing techniques - static approaches

- BinDiff https://www.zynamics.com/bindiff.html
 - o de-facto commercial tool
 - binary => Control-flow graph
 - graph isomorphism detection
 - heuristics for runtime performance



Existing techniques - dynamic approaches

- Blanket execution [USENIX Sec'14]
 - dynamically execute two given binaries
 - collect runtime information during execution
 - checking the semantic level equivalence based on the information



Existing techniques

- static analysis
 - low accuracy
 - syntax rather than semantics
- dynamic analysis
 - code coverage issue
 - poor scalability

new trend - Learning-based approaches!

Scalable Graph-based Bug Search for Firmware Images

Qian Feng, Rundong Zhou, Chengcheng Xu, Yao Cheng, Brian Testa, and Heng Yin

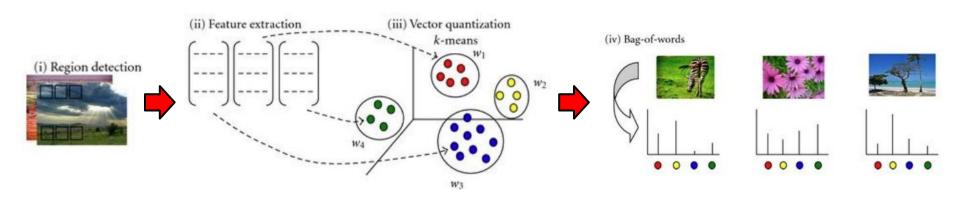
ACM CCS 2016

Motivation

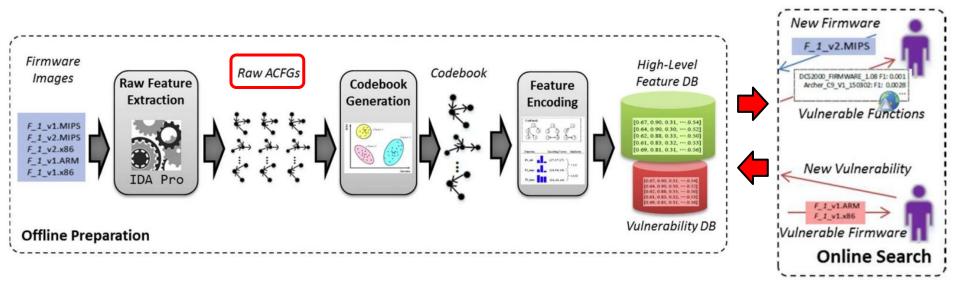
- Key challenge: cross-platform code search
 - string pattern or constant matching [Costin et al. USENIX Sec'14]
 - lack of generality
 - I/O pairs [Pewny et al. IEEE S&P'15]
 - lack of scalability
 - DiscovRe [Eschweiler et al. NDSS'16]
 - still not scalable enough
 - unreliable
- Biggest problem
 - graph matching is **EXPENSIVE!**
- How to achieve high performance matching?
 - graph representation learning

Graph Representation Learning

- Key idea:
 - learn from image processing
 - o use a high-dimensional vector, a.k.a. embeddings, to represent a graph



Genius Overview



Attributed Control Flow Graph

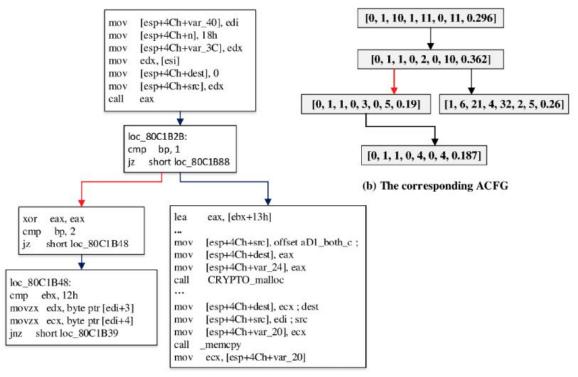
- Attributed Control Flow Graph
 - o a control-flow graph with features

Table 1: Basic-block level features.

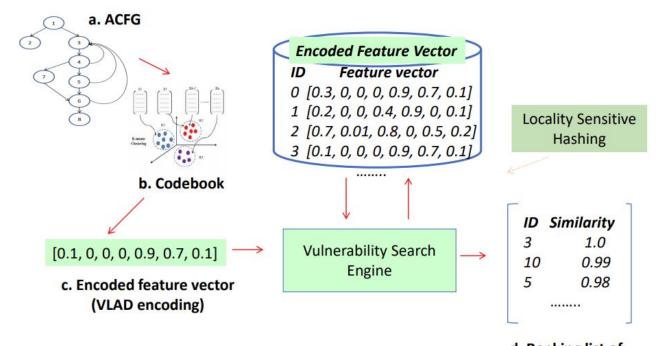
Туре	Feature Name	Weight (α)
Statistical Features	String Constants	10.82
	Numeric Constants	14.47
	No. of Transfer Instructions	6.54
	No. of Calls	66.22
	No. of Instructions	41.37
	No. of Arithmetic Instructions	55.65
Structural Features	No. of offspring	198.67
	Betweeness	30.66

Attributed Control Flow Graph

Example

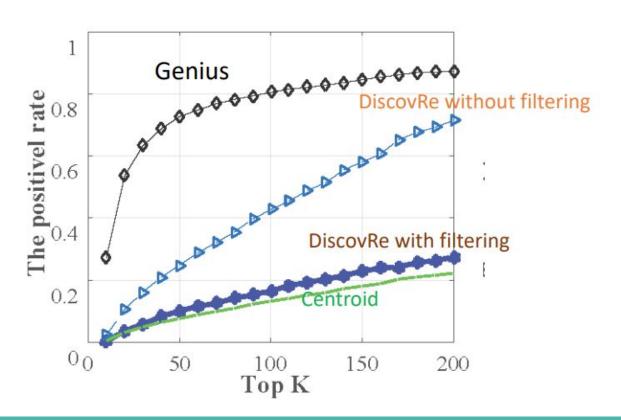


Index and Search

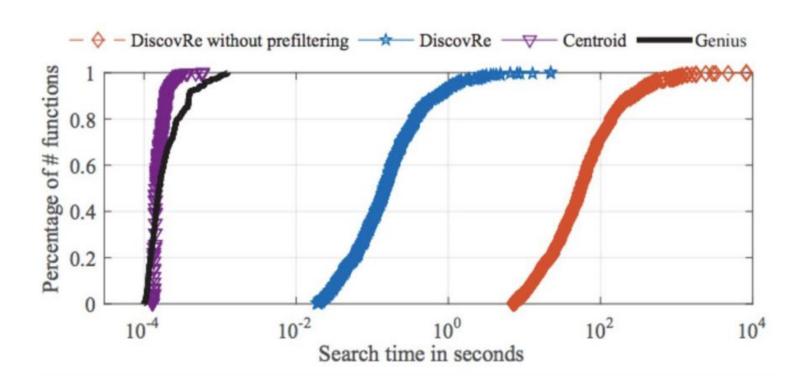


d. Ranking list of search results

Evaluation: True positive rate



Evaluation: Efficiency



Neural Network-based Graph Embedding for Cross-Platform Binary Code Similarity Detection

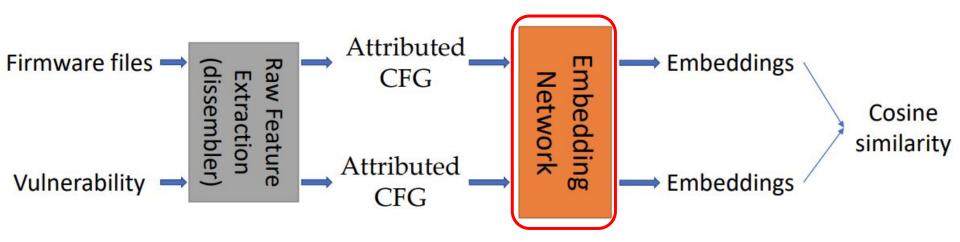
Xiaojun Xu, Chang Liu, Qian Feng, Heng Yin, Le Song, Dawn Song

ACM CCS 2017

Motivation

- Genius is great
 - more accurate: ACFG
 - faster: graph embeddings
- However
 - codebook generation can bring inaccuracy
 - graph representation learning is naive
- Key idea:
 - Can we use deep learning to learn graph embeddings?

Approach: Gemini

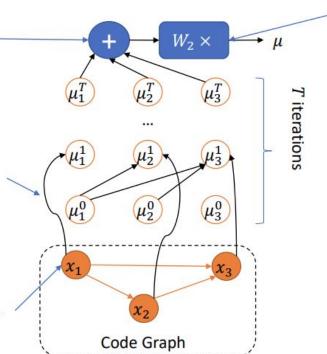


Embedding Network

3. After the last iteration, the embeddings on all vertexes are aggregated together

2. In each iteration, the embedding on each vertex is propagated to its neighbors

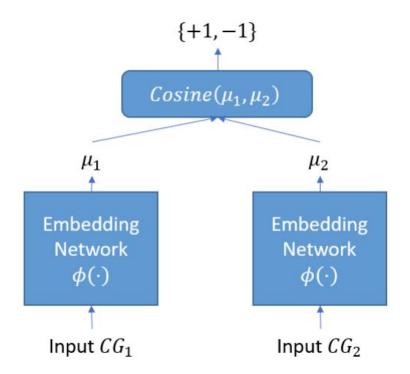
1. Initially, each vertex has an embedding vector computed from each code block



4. An affine transformation is applied in the end to compute the embedding for the graph

Training: Siamese Network

- Training data: a large number of functions
 - similar and dissimilar functions
- Train the network so that
 - similar functions will generate high similarity score
 - dissimilar functions will generate low similarity score



Evaluation: Efficiency

- Per function processing time
 - Genius: a few seconds to a few mins
 - Now: a few milliseconds

- Training time
 - Genius: > 1 week
 - Now: < 30 mins

Evaluation: Effectiveness

Function Name	Vendor	Firmware	Binary File	Similarity
ssl3 get_new_session_ticket		DAP-1562_FIRMWARE_1.00	wpa_supplicant.acfgs	
port_check_v6	D-Link	DES-1210-28_REVB_FIRMWARE_3.12.015	in.ftpd.acfgs	0.955408692
sub_42EE7C	TP-Link	TD-W8970B_V1_140624	racoon.acfgs	0.954742193
sub_42EE7C	TP-Link	TD-W8970_V1_130828	racoon.acfgs	0.954742193
prsa_parse_file	TP-Link	Archer_D5_V1_140804	racoon.acfgs	0.949814439
sub_432B8C	TP-Link	TD-W8970B_V1_140624	racoon.acfgs	0.949583828
sub_432B8C	TP-Link	TD-W8970_V1_130828	racoon.acfgs	0.949583828
ssl3_get_new_session_ticket	DD-wrt	dd-wrt.v24-23838_NEWD-2_K3.x_mega-WNR3500v2_VC	openvpn.acfgs	0.94668287
ucSetUsbipServer	TP-Link	WDR4900_V2_130115	httpd.acfgs	0.946312308
ssl3_get_new_session_ticket	Netgear	tomato-Cisco-M10v2-NVRAM32K-1.28.RT-N5x-MIPSR2-110-PL-Mini	libssl.so.1.0.0.acfgs	0.945933044
ssl3_get_new_session_ticket	Tomato_by_Shibby	tomato-K26-1.28.RT-MIPSR1-109-Mini	libssl.so.1.0.0.acfgs	0.945933044
ssl3_get_new_session_ticket	Tomato_by_Shibby	tomato-K26USB-1.28.RT-N5x-MIPSR2-110-VPN	libssl.so.1.0.0.acfgs	0.945932984
ssl3_get_new_session_ticket	Tomato_by_Shibby	tomato-E4200USB-NVRAM60K-1.28.RT-MIPSR2-110-PL-BT	libssl.so.1.0.0.acfgs	0.945932984
ssl3_get_new_session_ticket	Tomato_by_Shibby	tomato-E3000USB-NVRAM60K-1.28.RT-MIPSR2-110-BT-VPN	libssl.so.1.0.0.acfgs	0.945932984
ssl3_get_new_session_ticket	Tomato_by_Shibby	tomato-K26USB-1.28.RT-MIPSR1-109-AIO	libssl.so.1.0.0.acfgs	0.945932984
ssl3_get_new_session_ticket	Tomato_by_Shibby	tomato-Netgear-3500Lv2-K26USB-1.28.RT-N5x109-AIO	libssl.so.1.0.0.acfgs	0.945932984
ssl3_get_new_session_ticket	Tomato_by_Shibby	tomato-E4200USB-NVRAM60K-1.28.RT-MIPSR2-109-AIO	libssl.so.1.0.0.acfgs	0.945932984
ssl3_get_new_session_ticket	Tomato_by_Shibby	tomato-E1550USB-NVRAM60K-1.28.RT-N5x-MIPSR2-110-Nocat-VPN	libssl.so.1.0.0.acfgs	0.945932984
ssl3_get_new_session_ticket	Tomato_by_Shibby	tomato-K26USB-1.28.RT-N5x-MIPSR2-115-PL-L600N	libssl.so.1.0.0.acfgs	0.945932984
ssl3_get_new_session_ticket	Tomato_by_Shibby	tomato-E1550USB-NVRAM60K-1.28.RT-N5x-MIPSR2-110-BT-VPN	libssl.so.1.0.0.acfgs	0.945932984
ssl3_get_new_session_ticket	Tomato_by_Shibby	tomato-E3000USB-NVRAM60K-1.28.RT-MIPSR2-108-PL-VPN	libssl.so.1.0.0.acfgs	0.945932984
ssl3_get_new_session_ticket	Tomato_by_Shibby	tomato-E1550USB-NVRAM60K-1.28.RT-N5x-MIPSR2-110-Mega-VPN	libssl.so.1.0.0.acfgs	0.945932984
ssl3_get_new_session_ticket	Tomato_by_Shibby	tomato-E1200v2-NVRAM64K-1.28.RT-N5x-MIPSR2-108-PL-Max	libssl.so.1.0.0.acfgs	0.945932984
ssl3_get_new_session_ticket	Tomato_by_Shibby	tomato-K26USB-1.28.RT-MIPSR1-109-Mega-VPN	libssl.so.1.0.0.acfgs	0.945932984
ssl3_get_new_session_ticket	Tomato_by_Shibby	tomato-E3000USB-NVRAM60K-1.28.RT-MIPSR2-109-Big-VPN	libssl.so.1.0.0.acfgs	0.945932984
ssl3_get_new_session_ticket	Tomato_by_Shibby	tomato-E4200USB-NVRAM60K-1.28.RT-MIPSR2-108-PL-Nocat-VPN	libssl.so.1.0.0.acfgs	0.945932984
ssl3_get_new_session_ticket	Tomato_by_Shibby	tomato-Netgear-3500Lv2-K26USB-1.28.RT-N5x110-ND-AIO	libssl.so.1.0.0.acfgs	0.945932984
ssl3 get new session ticket	Tomato by Shibby	tomato-E4200USB-NVRAM60K-1.28.RT-MIPSR2-109-Nocat-VPN	libssl.so.1.0.0.acfgs	0.945932984

- Among top 50 vulnerabilities
 - 42/50 can be identified
 - o Genius: 10/50

DeepBinDiff: Learning Program-Wide Code Representations for Binary Diffing

Yue Duan, Xuezixiang Li, Jinghan Wang, and Heng Yin

NDSS 2020

Motivation

- Existing techniques
 - No efficient binary diffing at basic block level
 - Genius and Gemini: function comparison
 - No program-wide contextual information
 - why useful?
 - Heavily rely on labelled training data
 - balanced training data can be hard

System Design

program-wide contextual info learning **Embedding** Cod Input Pre-processing Output Generation CFG gene Complete unsupervised al matching binary 1 learning approach diffing results k-hop greedy token embedding 0.335, -0.93, 0.1189, ... binary 2 matching **→** (0.052, -0.0° -1.8e-06, 0.092, 0.06, ... model 0.15, 0.13 0.55, 0.656, 0.33, .. basic block feature vectors embeddings embeddings efficient matching semantic info learning

calculate *similarity*

Key Idea: Natural Language Processing

binaries



Patricia I., McEldowney

Le professor squi entegies Pangliai comme langue trangira s besin de plus d'information nur l'Orporation de carigines grammatiches que des qui est a sa disposition dans le grammatic description de la langue angliate. Il devrais possovir s'apopter dans son entispement sur une Grammatie dichesiques (predichesig gramma). Cell centure dans le domain de l'emploid servation de la frança de l'apopter dans sons langue trangire commentent un grant fundre de faire. Cet qui de caric de developage de la compart de caracterité de developage de l'apopter de caracterité entre de developage de l'apopter de caracterité de l'apopter de la caracterité de l'apopter de l'apopter de l'apopter de l'apopter de l'apopter de la caracterité de l'apopter de l

In any grammatical area the teacher of English to non-native speakers needs a great seal of information which be cannot easily find in an ordinary descriptive grammar of English. This type of grammar does not often contain, for instance, explicit assuments about the useful contract of the english statement of the englis

In the paper, the phrase "article usage" refers to usage concerned with the presence or absence of the items a, the, -s and some.

random walks



Identify the subject and predicate in these SIMPLE sentences.

- 3. Cindy and Sue auditioned for the lead role in the play.
- 2. The kittens were adopted by the family.
- 3. Peanut butter and jelly sandwiches are my favorite.
- 4. The committee decorated the gym for Friday night's dance.
- 5. The surprise party was organized by Wendy's two best friends.

tokens





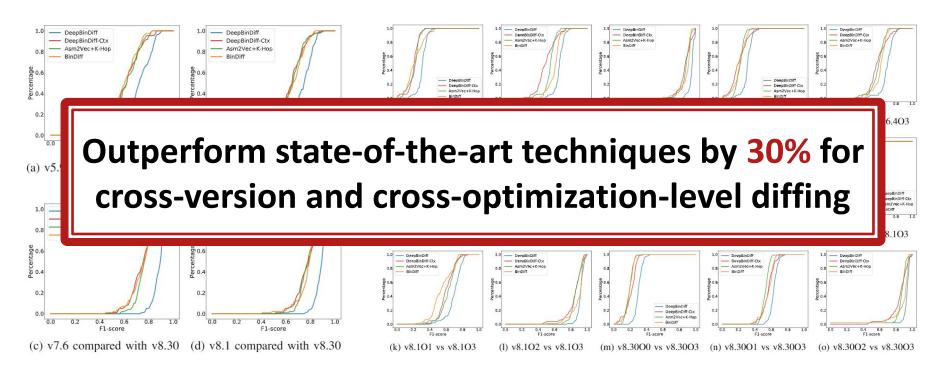
Program-wide Contextual Info Learning



Program-wide Contextual Info Learning

feature vector **Graph Representation Learning** 0.053, 0.16, 0.032 ... 0.12, 0.44, -0.009 ... 0.411, -0.2206, 0.4 ... 0.55, 0.656, 0.33 ... 0.055. 0.004. -0.07 ... 0.07, -0.314, 0.305 ... 0.335, -0.93, 0.1189 ... -1.8e-06, 0.092, 0.06 ... basic block embeddings semantics & contextual info merged graph calculate basic block similarity

Evaluation



Thank you! Question?