

An Extensive Study on the Binary Diffing Problem

12012109 安钧文

12010336 黄慧惠

Supervisor: Prof. Yuqun Zhang

Content



- Background
- Related Work

- Research Questions
- Proposed Approach

Binary Diffing



- Input two binary files
- Output matches
 - Added/Deleted/Matched
- Granularity
 - Function/Basic Block/Instruction

Motivation



- Efficient patching: Reduce the size of the patch and make it faster to download and install.
- Malware analysis: Compare different versions of software, analyze changes and identify vulnerabilities.
- Version control

Traditional Approach



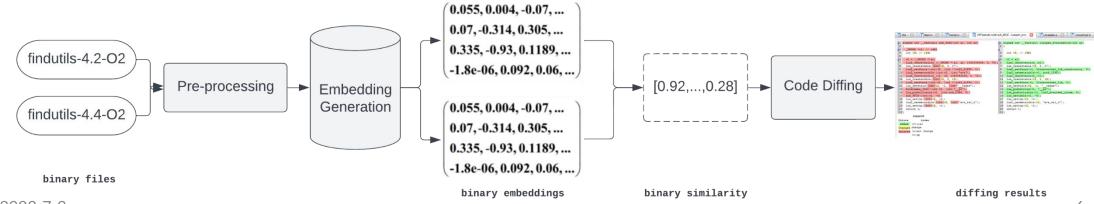
• Direct matching on call graphs and control-flow graphs

• Focuses on **syntax** of instructions

Learning-based Approach



- Pre-processing:
 - disassembly binary code, tokenize
- Embedding generation
- Semantic similarity calculation
- Code diffing
 - graph matching, network alignment



Dilemmas



Code structure

- change the order of code execution
- change the size of code
- introduce new instructions

Time complexity: computationally expensive, especially for large files or complex software.

Content



- Background
- □ Related Work

- Research Questions
- Proposed Approach

Binary Similarity Detection



Natural Language Processing based

- BinShot (ACSAC' 22)
- jTrans (ISSTA' 22)
- PalmTree (CCS' 21)
- InnerEye (NDSS' 19)
- Asm2Vec (S&P' 19)

Combined

- OrderMatters (AAAI' 20)
- DeepBinDiff (NDSS' 20)

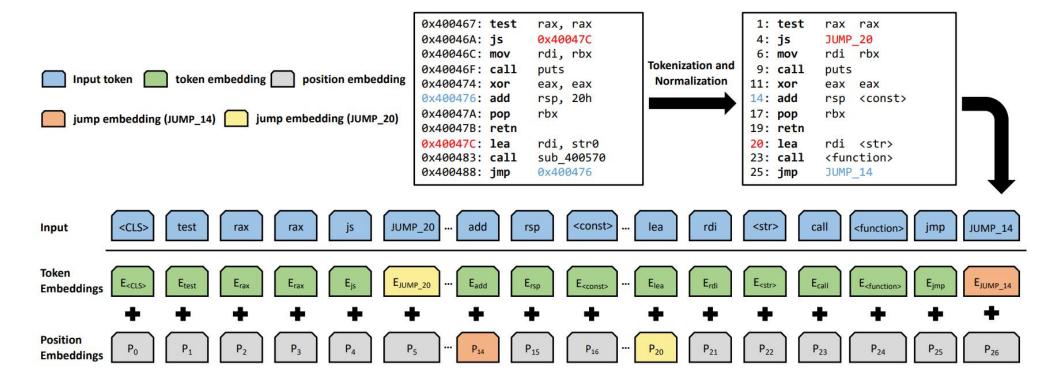
Graph Representation Learning based

- XBA (ISSTA' 22)
- Asteria (DSN' 21)
- GMN (ICML' 19)
- VulSeeker (ASE' 18)
- Gemini (CCS' 17)

jTrans - BERT (ISSTA' 22)



 Model assembly instructions as natural language tokens, but with considerations of code semantic



DeepBinDiff - Graph Embedding



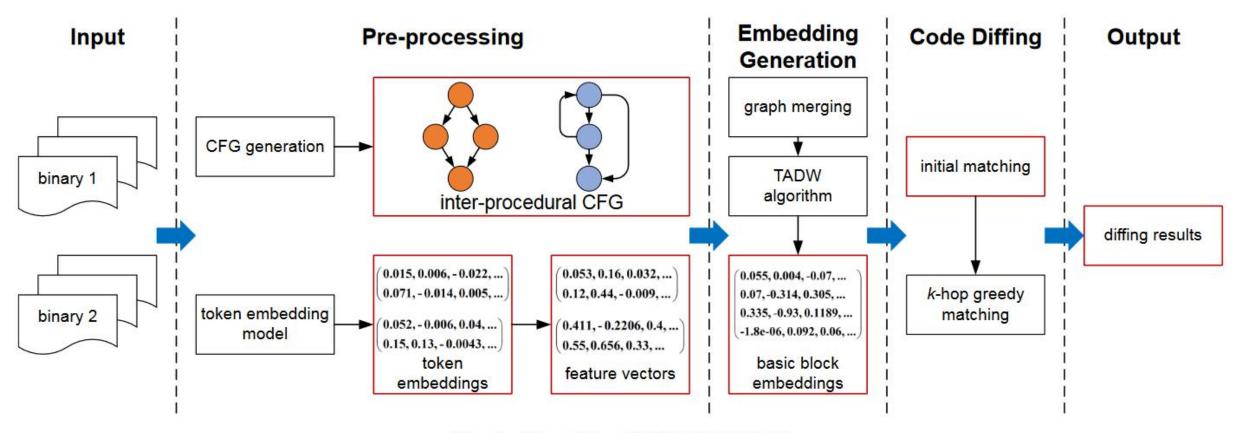


Fig. 1: Overview of DEEPBINDIFF.

Diffing Approaches



- Diffing tools
 - Diaphora
 - BinDiff

Maximum Weight Matching (MVM)

Maximum Common Edge Subgraph (MCS)

- Hungarian Algorithm
- DeepBinDiff (NDSS' 20)
- BinDiff

Network Alignment Problem (NAP)

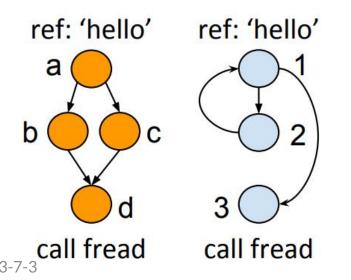
- IsoRank
- QBinDiff (ASE' 21)

$$\alpha \mathbf{x}^T Q_1 \mathbf{x} + (1 - \alpha) \mathbf{x}^T Q_2 \mathbf{x}.$$

DeepBinDiff - Code Diffing



- Expand neighboring edges
- Match the most similar pairs
- Implicitly solving maximum common subgraph problem



Algorithm 1 k-Hop Greedy Matching Algorithm

```
1: Set_{virtual nodes} \leftarrow \{virtual nodes from merged graphs\}
 2: Set_{initial} \leftarrow ComputeInitialSet(Set_{virtualnodes})
 3: Set_{matched} \leftarrow Set_{initial}; Set_{currPairs} \leftarrow Set_{initial}
 5: while Set_{currPairs} != empty do
         (node_1, node_2) \leftarrow Set_{currPairs}.pop()
         nb_{node_1} \leftarrow \text{GetKHopNeighbors}(node_1)
         nb_{node_2} \leftarrow \text{GetKHopNeighbors}(node_2)
         newPair \leftarrow FindMaxUnmatched(nb_{node_1}, nb_{node_2})
         if newPair != null then
             Set_{matched} \leftarrow Set_{matched} \cup newPair
11:
             Set_{currPairs} \leftarrow Set_{currPairs} \cup newPair
         end if
14: end while
15: Set_{unreached} \leftarrow \{ basic blocks that are not yet matched \}
16: \{Set_m, Set_i, Set_d\} \leftarrow LinearAssign(Set_{unreached})
17: Set_{matched} \leftarrow Set_{matched} \cup Set_m
    output Set_{matched}, Set_i, Set_d as the diffing result
```

Content



- Background
- Related Work

- Research Questions
- Proposed Approach

Dataset



- Findutils
 - 4 binary files
 - 4 versions (2005-2022 span of 17 years)
 - Compiled with GCC v5.4, Ubuntu 18.04, O1 optimization
 - Stripped symbol table

find
locate
updatedb
xargs

Ground truth



- Extracted from source code, manually verified
- Mapped to function address pairs
- Focus on soundness rather than completeness
 - E.g. (00003F70, 00006320)

Experiment Setup



- Dataset
 - Findutils
- Decompilation
 - IDA pro v7.6
- Function similarity measurement
 - jTrans (ISSTA' 22)

Metrics



- Precision exclude unknown matches
- Recall
- F1

 $||M_c||$: True Positive

 $||M - M_u - M_c||$: False Positive

||G||: Ground truth

$$Precision = \frac{||M_c||}{||M_c|| + ||M - M_u - M_c||}$$

$$Recall = \frac{||M_c||}{||G||}$$

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Research Question 1



- How do different diffing algorithms with the same similarity results perform?
- Evaluation Target:
 - Hungarian Algorithm (MWM)
 - K-hop matching (MCS)
 - IsoRank (NAP)

Results



Table 1: Result of different diffing algorithms

Version	Precision			Recall			F1-score			
	Hungarian	K-hop	IsoRank	Hungarian	K-hop	IsoRank	Hungarian	K-hop	IsoRank	
v4.2.33 - v4.9.0	0.894	0.909	0.931	0.747	0.759	0.684	0.814	0.827	0.788	
v4.4.1 - v4.9.0	0.876	0.893	0.818	0.795	0.662	0.583	0.833	0.760	0.679	
v4.6.0 - v4.9.0	0.959	0.942	0.884	0.897	0.784	0.690	0.927	0.856	0.775	

Research Question 2



- What are the external factors that affect diffing performance?
 - Function Inlining
 - External function references
 - Stripped vs. Unstripped

External Function References

Southern University of Science and Technology

- Same intruction-jmp
- Same embedding content
- Could lead to random matching
- Lower presicion

.fopen

```
; Attributes: thunk
; FILE *fopen(const char *filename, const char *modes)
_fopen proc near
jmp cs:fopen_ptr
_fopen endp
```

.error

```
; Attributes: thunk
; void error(int status, int errnum, const char *format, ...)
_error proc near
jmp cs:error_ptr
_error endp
```

```
.strpbrk - .tolower
.__freading - .pthread_mutex_unlock
.fchdir - .iswalnum
.gnu dev major - .wcrtomb
.realloc - .fflush
.fdopen - .getmntent
.setlocale - .setmntent
.poll - .nl_langinfo
.strftime - .endpwent
.memmove - .sscanf
.error - .mktime
.memrchr - .strpbrk
.waitpid - .__freading
.open - .fchdir
.access - .gnu_dev_major
.fseeko - .fdopen
.fopen - .setlocale
.sysconf - .timegm
.strtoumax - .poll
```

Stripped Symbol Table



Table 2: K-hop matching performance of symbol table stripping

Version	Unstripp	\mathbf{ed}		Stripped				
	Precision	Recall	F1-score	Precision	Recall	F1-score		
v4.2.33 - v4.9.0	0.923	0.732	0.807	0.909	0.759	0.829		
v4.4.1 - v4.9.0	0.901	0.739	0.772	0.893	0.662	0.760		
v4.6.0 - v4.9.0	0.946	0.810	0.844	0.942	0.784	0.856		

Table 3: Diaphora performance of symbol table stripping

Version	Unstripp	ed		Stripped				
	Precision	Recall	F1-score	Precision	Recall	F1-score		
v4.2.33 - v4.9.0	- v4.9.0 0.955		0.941	0.947	0.455	0.615		
v4.4.1 - v4.9.0	0.958	0.931	0.944	0.940	0.523	0.672		
4v.6.0 - v4.9.0	0.958	0.930	0.943	0.980	0.661	0.791		

Research Question 3



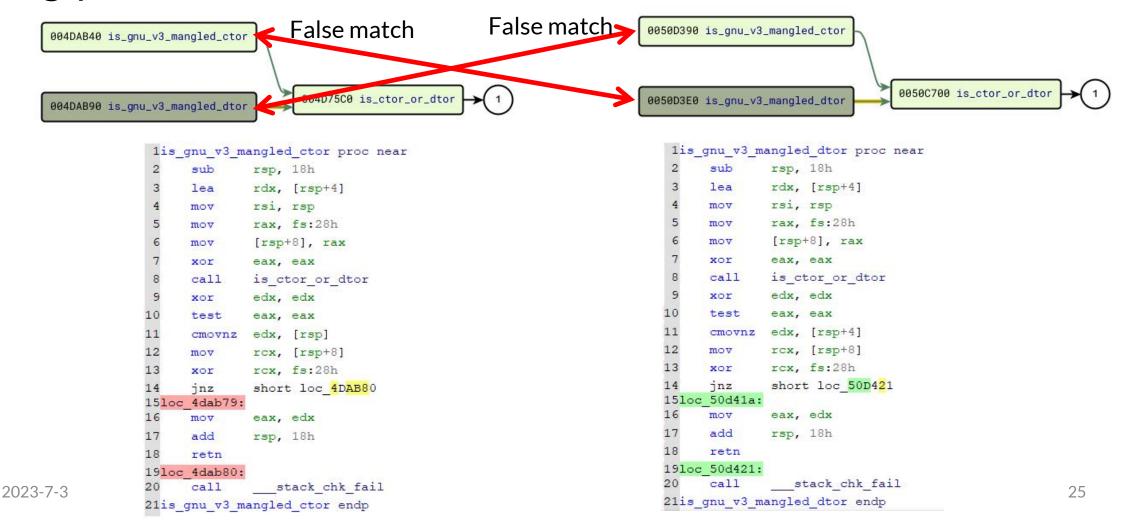
24

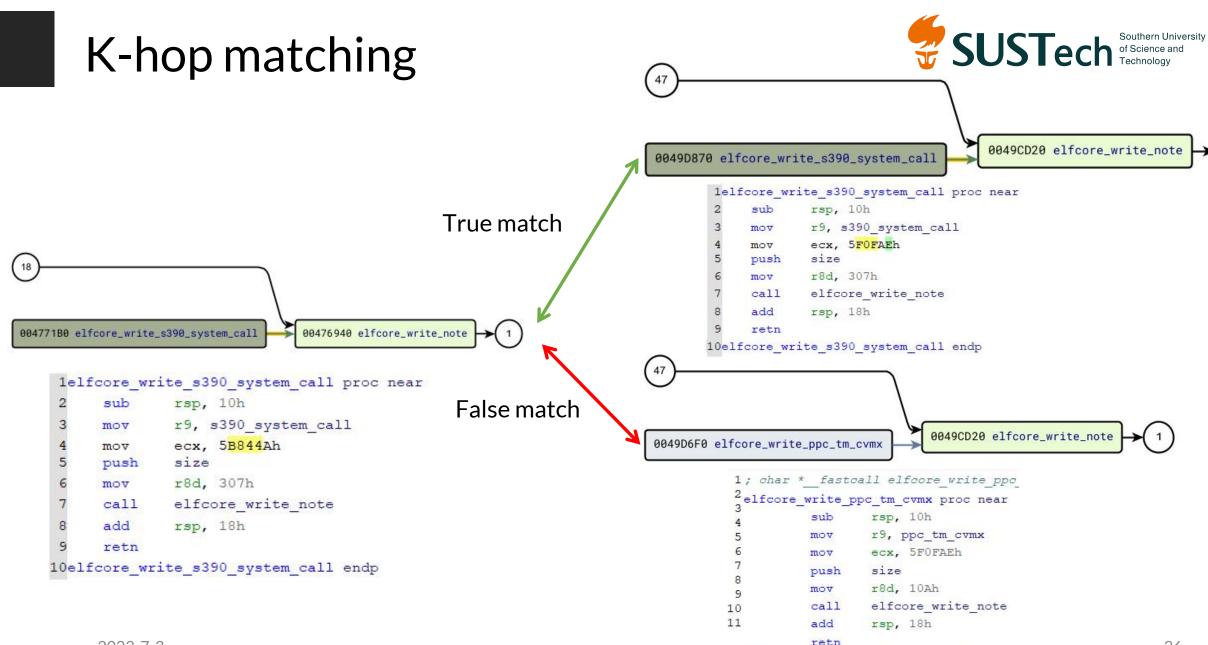
- What is the cause of false positive results?
- Evaluation Target:
 - Hungarian Algorithm (MWM)
 - K-hop matching (MCS)
 - IsoRank (NAP)

Hungarian Algorithm



Wrongly cross-match



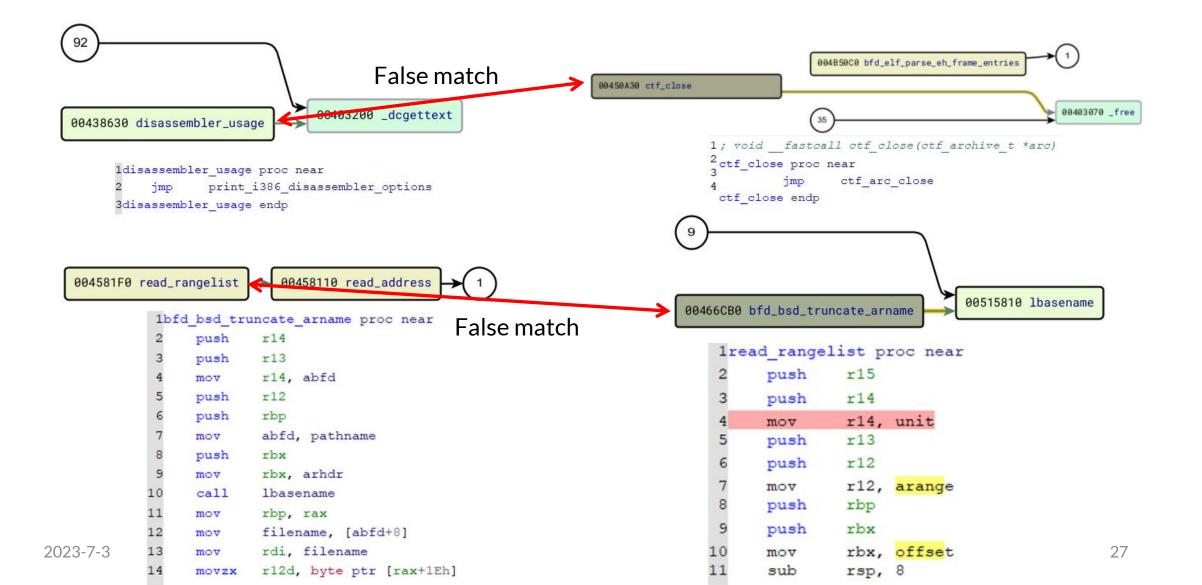


2023-7-3

elfcore_write_ppc_tm_cvmx endp

IsoRank





Content



- Background
- Related Work

- Research Questions
- Proposed Approach

Approach



• Intuition:

- Across version changes, major functions are preserved and easily distinguishable
- Code changes tend to happen around major functions (e.g., refactoring)
- Instead of aligning from external function references (as in DeepBindiff), start directly inside the call graph

Approach



- Seed-and-Extend
- Combine idea of both Hungarian algorithm and K-hop matching
- Leverage both <u>node</u> and <u>network</u> information
- Use heuristic to approximate global network alignment
 - Utilize as much starting points as possible

Approach



- Step 1 Find initial alignment based on similarity threshold θ
 - match distinguishable major functions
- Step 2 K-hop matching on initial alignments
 - match "hard" cases with graph's assistance
- K = 2 due to dense call graph

```
Algorithm 1 Seed-and-Extend
 1: procedure SEEDANDEXTEND(G_1, G_2, \theta, k)
        initialAlignment \leftarrow \emptyset
 2:
        for n_1 \in G_1 do
 3:
            initialPair \leftarrow findMaxSim(G_2, \theta)
 4:
            if initial Pair! = null then
 5:
               initialAlignment.add(initialPair)
 6:
            end if
 7:
        end for
 8:
        currentAligned, resultAligned \leftarrow initialAlignment
 9:
        while currentAligned is not empty do
10:
            i, j \leftarrow currentAligned.pop()
11:
            neighbors_i \leftarrow \text{findTwoHopNeighbors}(i)
12:
            neighbors_i \leftarrow \text{findTwoHopNeighbors}(j)
13:
            maxPair \leftarrow findMaxUnmatched(neighbors_i, neighbors_i)
14:
            resultAlignment.add(maxPair)
15:
```

end while

18: end procedure

return resultAligned

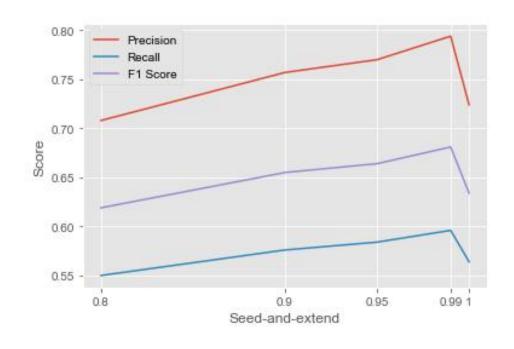
16:

17:

Evaluation



- How to determine the threshold?
- Use objdump as evaluation binary
 - Call graph is more complex
 - Function number is bigger
- Experimented on various θ value



Evaluation



Performance of Seed-and-Extend

- Competent performance on both software
- Better performance on bigger scale binary

Binary	Version	Precision				Recall				F1-score			
		Hungarian	K-hop	IsoRank	S-E	Hungarian	K-hop	IsoRank	S-E	Hungarian	K-hop	IsoRank	S-E
findutils	v4.2.33 - v4.9.0	0.894	0.909	0.931	0.882	0.747	0.759	0.684	0.759	0.814	0.827	0.788	0.816
	v4.4.1 - v4.9.0	0.876	0.893	0.818	0.896	0.795	0.662	0.583	0.795	0.833	0.760	0.679	0.842
	v4.6.0 - v4.9.0	0.959	0.942	0.884	0.941	0.897	0.784	0.690	0.874	0.927	0.856	0.775	0.906
objdump	v2.25 - v2.40	0.690	0.719	0.857	0.794	0.544	0.521	0.504	0.596	0.608	0.623	0.635	0.681

Evaluation



- What are possible drawbacks?
- Heavily depends on similarity results
- Unable to match similar functions with identical call graph



References



- [1] Zeping Yu, Rui Cao, Qiyi Tang, Sen Nie, Junzhou ouang, and Shi Wu. Order Matters: Semantic-Aware Neural Networks for Binary Code Similarity Detection. Proceedings of the AAAI Conference on Artificial Intelligence, 34(01):1145–1152, April 2020.
- [2] H. Wang, W. Qu, G. Katz, W. Zhu, Z. Gao, H. Qiu, J. Zhuge, and C. Zhang, "jtrans: jump-aware transformer for binary code similarity detection," in Proceedings of the 31st ACM SIGSOFT International Symposium on Software Testing and Analysis, 2022, pp. 1–13
- [3] Yue Duan, Xuezixiang Li, Jinghan Wang, and Heng Yin. DeepBinDiff: Learning Program-Wide Code Representations for Binary Diffing. In Proceedings of Network and Distributed System Security Symposium, 2020.
- [4] E. Mengin and F. Rossi, "Binary Diffing as a Network Alignment Problem via Belief Propagation," 2021 36th IEEE/ACM International Conference on Auto-mated Software Engineering (ASE), Melbourne, Australia, 2021, pp. 967-978, doi: 10.1109/ASE51524.2021.9678782.
- [5] F. Zuo, X. Li, P. Young, L. Luo, Q. Zeng, and Z. Zhang, "Neural Machine Translation Inspired Binary Code Similarity Comparison beyond Function Pairs," in Proceedings 2019 Network and Distributed System Security Symposium. Reston, VA: Internet Society, 2019
- [6] F. Zuo, X. Li, P. Young, L. Luo, Q. Zeng, and Z. Zhang, "Neural Machine Translation Inspired Binary Code Similarity Comparison beyond Function Pairs," in Proceedings 2019 Network and Distributed System Security Symposium. Reston, VA: Internet Society, 2019.
- [7] Harold W. Kuhn, "The Hungarian Method for the assignment problem", Naval Research Logistics Quarterly, 2: 83–97, 1955. Kuhn's original publication.