A Tree Distance Function Based on Multi-sets

Protecting Open Source Software with Trees

A. Müller K. Hirata T. Shinohara

Department of Artificial Intelligence
Kyushu Institute of Technology (Iizuka, Japan)

ALSIP 2008 (Osaka, Japan)

Outline

1. Introduction
   - Motivation: Binary Program Matching
2. Proposed Tree Distance Function
   - Concepts
   - Related Works
   - Distance Definition
   - Examples
   - Characteristics
3. Case Study
   - Setup
   - Results
4. Conclusions

Introduction

Tree structured data, main contributions

- XML, RNA structures
- Approximate Binary Program Matching (ABPM)
  - Detect program theft (OSS license violations)
  - Detect common low level functionality
- Metrics are desirable:
  - $d(T_1, T_2) = 0 \iff T_1 = T_2$
  - Triangle inequality (MAM can be employed)
- Formalized an $O(n^2)$ metric (*mtd*) proposed before. Müller, Shinohara (2006)
  - Other functions are not suitable for ABPM
  - Designed for ABPM
  - Experimentally studied properties

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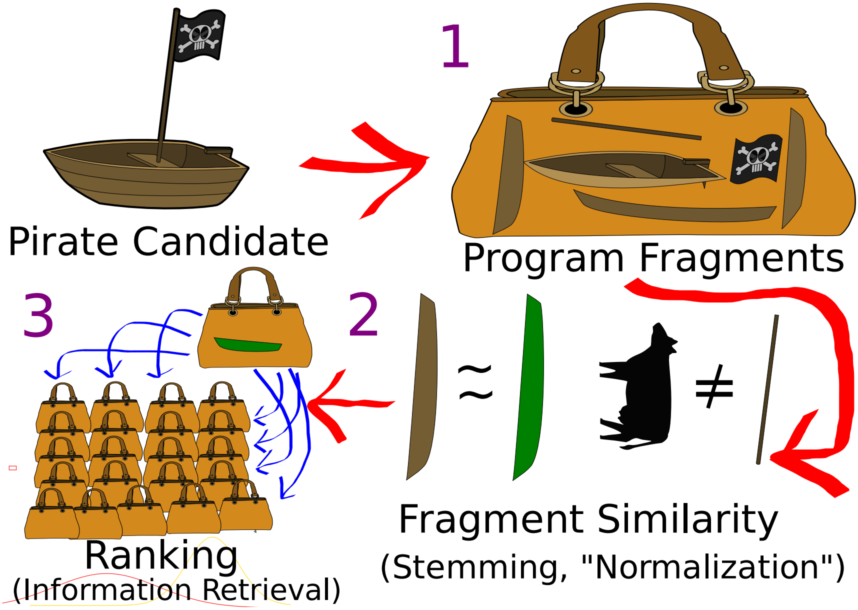
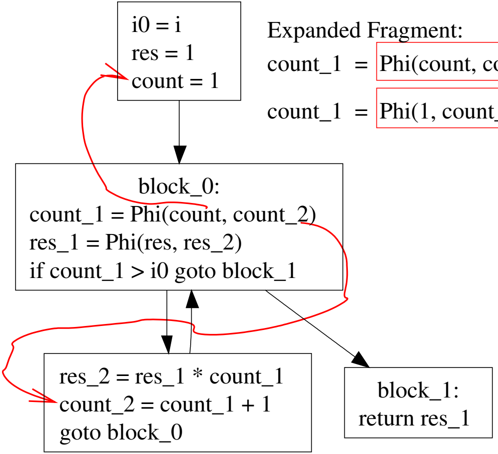
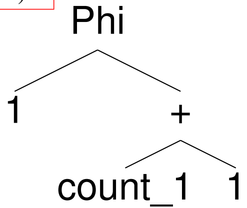

Pirate Candidate
1
Program Fragments
2
≈
≠
Fragment Similarity
(Stemming, "Normalization")
3
Ranking
(Information Retrieval)



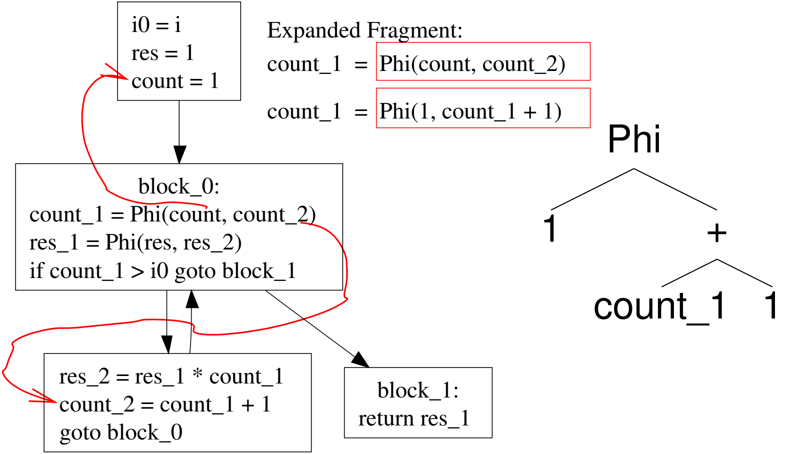
Expanded Fragment:

count_1 = Phi(count, count_2)

count_1 = Phi(1, count_1 + 1)



- Output: machine instruction trees
- Complete Subtrees required
- Deeper change, greater semantic change



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Concepts

Concepts employed during the presentation

- Multi-set additive union: $\uplus$
  - $\{A, A, B\} \uplus \{A, B, C\} = \{A, A, A, B, B, C\}$
- Multi-set union: $\sqcup$
  - $\{A, A, B\} \sqcup \{A, B, C\} = \{A, A, B, C\}$
- Multi-set intersection: $\sqcap$
  - $\{A, A, B\} \sqcap \{A, B, C\} = \{A, B\}$

Definition

Let T be a tree and v a node in T.
A *complete subtree* of T at v is a subtree of T of which its root is v and that contains all descendants of v.

- Complete subtree preserves semantics

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Overview

Distance Functions

- TED Tai (1979)
  - Insert, delete, rename operations
  - Minimum edit script
  - Fastest Algorithm: $O(n^3)$. Demaine *et al.*(2007)
  - Changes are treated equally, not good for ABPM
- Extension of edit operations. Chawathe *et al.*(1997)
  - Operations on subtrees: move, copy, glue (inverse of copy)
  - NP-Complete, Heuristic $O(n^3)$
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Overview (2)

Distance Functions

- Constrained edit distance: Wang, Zhang (2005)
  - Like *ted* but equal subtrees are matched first
  - $O(n^2)$, complete subtrees not preserved
- N-Gram Based: Yang *et al.*(2005), Ohkura *et al.*(2004)
  - Partition trees, match those parts
  - Semantics are lost
  - $O(n)$
- No suitable distance functions available, we implemented *mtd*

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mtd

Tree distance function based on multi-sets

- $s(T)$: multi-set of all complete subtrees of T
- $n(T)$: multi-set of all the nodes of T

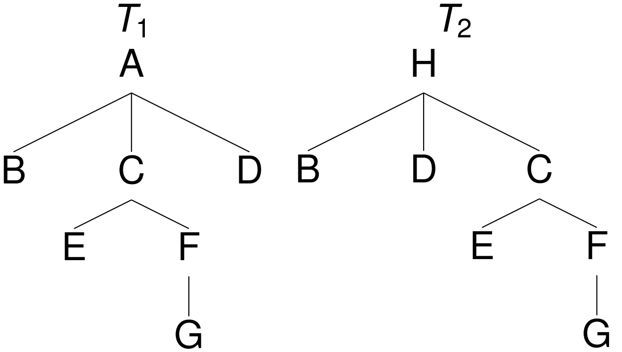
$$\delta(A, B) = |A \sqcup B| - |A \sqcap B|, \quad (1)$$

$$d_s(T_1, T_2) = \delta(s(T_1), s(T_2)), \quad (2)$$

$$d_n(T_1, T_2) = \delta(n(T_1), n(T_2)), \quad (3)$$

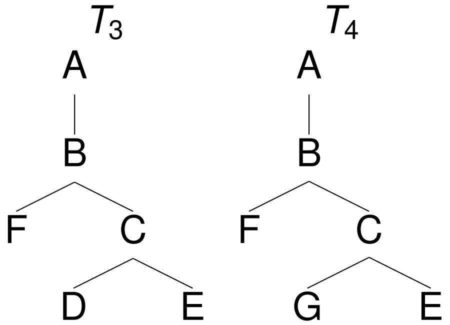
$$mtd(T_1, T_2) = \frac{d_s(T_1, T_2) + d_n(T_1, T_2)}{2} \quad (4)$$

Outline



$$s(T_1) = \{A(B, C(E, F(G)), D), B, C(E, F(G)), E, F(G), G, D\}$$
$$s(T_2) = \{H(B, D, C(E, F(G))), B, C(E, F(G)), E, F(G), G, D\}$$
$$n(T_1) = \{A, B, C, E, F, G, D\}$$
$$n(T_2) = \{H, B, C, E, F, G, D\}$$

$$|s(T_1) \sqcap s(T_2)| = 6 \quad mtd(T_1, T_2) = \frac{(8-6)+(8-6)}{2} = 2$$
$$|n(T_1) \sqcap n(T_2)| = 6 \quad ted(T_1, T_2) = 3$$



$s(T_3) = \{A(B(F, C(D, E))), B(F, C(D, E)), F, C(D, E), D, E\}$
$s(T_4) = \{A(B(F, C(G, E))), B(F, C(G, E)), F, C(G, E), G, E\}$
$n(T_3) = \{A, B, F, C, D, E\}$
$n(T_4) = \{A, B, F, C, G, E\}$

$|s(T_3) \sqcap s(T_4)| = 2 \quad mtd(T_3, T_4) = \frac{(10-2)+(7-5)}{2} = 5$

$|n(T_3) \sqcap n(T_4)| = 5 \quad ted(T_3, T_4) = 1$

- Complete subtrees are necessary

Outline

Properties

Characteristics of *mtd*

- *mtd* is an $O(n^2)$ metric
- Result is always in $\mathbb{N}$
- d_n same root nodes, different children
- d_s preserves semantic chunks of expressions
- d_s: very sensitive to changes
- d_n: trees become close to each other
- Is the average between d_s and d_n useful?
  - Approximate program matching: only d_s is enough
  - Minimum and maximum values become smaller

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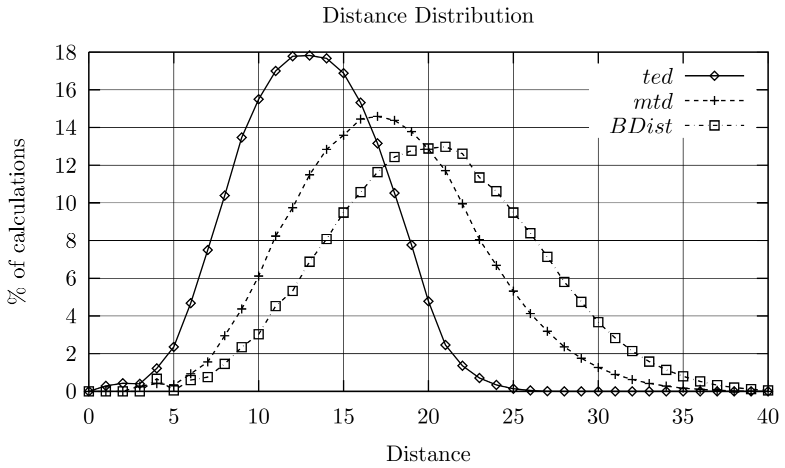
Setup

Experiment Definition

- 244668 trees
- Average depth: 4.75
- Average number of nodes: 11.11
- Randomly selected 1000 trees (queries)
    - Compare them against the dataset
- Distance functions:
    - *ted* $O(n^3)$ Demaine (2007), *BDist* $O(n)$ Yang (2005), *mtd* $O(n^2)$
    - Intel(R) Xeon(R) CPU 2.66 G-Hz with 4 processors

Distribution between data and queries



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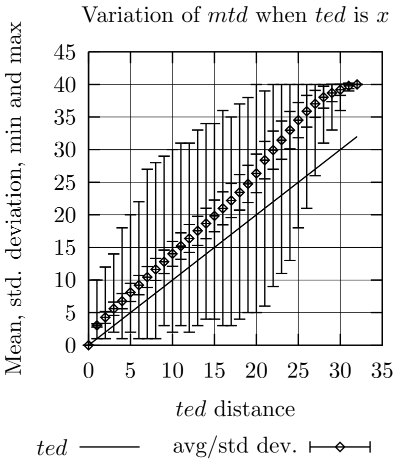
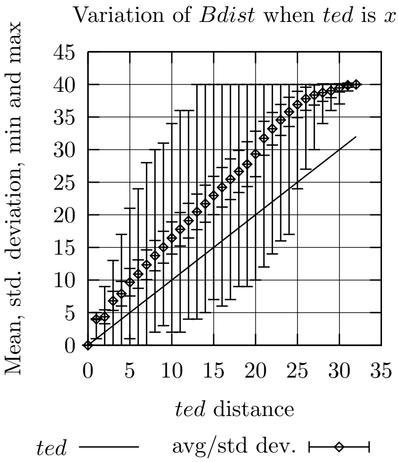
Variation of *mtd* and *BDist*

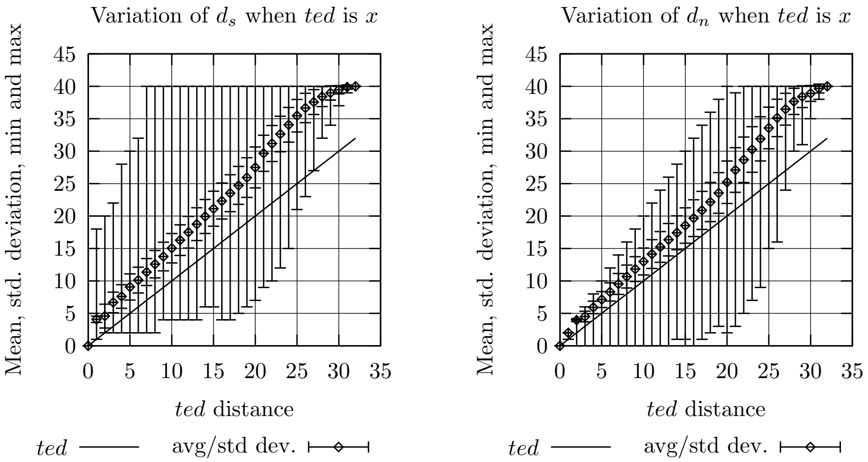
On average similar, but *mtd* is a metric



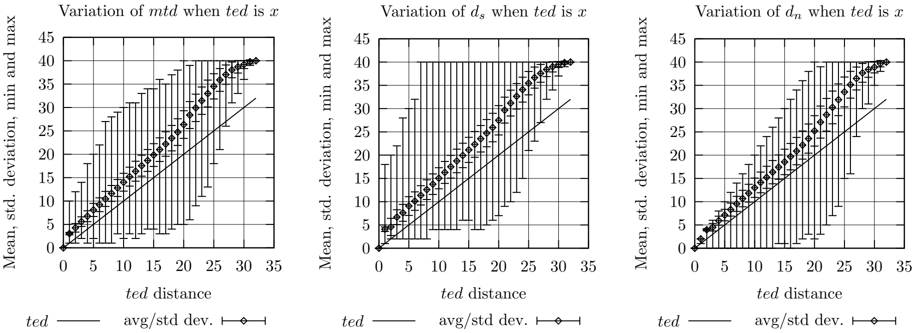


Variation of d_s and d_n

On average d_n is closer to *ted*!



Comparing d_n, d_s and mtd



Benchmarks

Execution time results

- Queries: 1000
- DB: 244668

Function	Total	Per Function Call	Improvement over *ted*
mtd	7.4 min.	0.001 millisec.	689x
BDist	8 min.	0.001 millisec.	637x
ted	85 hr.	1 millisec.	1x

- SMAP + Spatial Index / High Dimensional Index

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OBSearch!

Open Source Metric Access Method (MAM)

- Nearest neighbor
- S-Map and P+Tree
- GPL 2.0
- http://obsearch.net

Conclusions

mtd is fast, and very sensitive to changes.

- Introduced an $O(n^2)$ metric, *mtd*
  - Tuned to perform ABPM
- Our implementation is as fast as *BDist*
- Suffix trees can make *mtd* $O(n)$, Vishwanathan (2002)
- Future work:
  - Analyze other distance functions (ABPM)
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