Applications of Graph Integration to Function Comparison and Malware Classification

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Agenda

1. Overview of our Vectorization Method
2. The .NET Framework and Common Language Runtime (CLR)
3. Decompilation
4. Graph Integration
5. Results

Overview of our Vectorization Method

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Overall Goal

Construct a vectorization method to be leveraged by a classifier on .NET files

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1. Decompile(file) $\longrightarrow \{G\}$

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3. Compute antiderivatives of functions defined in previous step
4. Compute component-wise mean/std of antiderivatives across all G resulting from decompilation of the given file

The .NET Framework and Common Language Runtime (CLR)

.NET Framework - two main components

Framework Class Library (FCL)

- user interface
- data access
- database connectivity
- cryptography
- web application development

Common Language Runtime (CLR)

- is an application virtual machine which provides

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Common Language Runtime (CLR)

- is an application virtual machine which provides
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- compilation of high-level .NET code results in an Intermediate Language Binary
- the CLR JITs the code from IL to machine code run on the cpu

Decompilation

Decompilation

Definition

Decompilation is a program transformation by which compiled code is transformed into a high-level human-readable form.

Definition

An *Abstract Syntax Tree* is a tree representation of the abstract syntactic structure of the source code, where each node denotes a construct occurring in the source code.

Program control flow is understood by studying the structure of two types of control flow graphs resulting from decompilation.

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Program control flow is understood by studying the structure of two types of control flow graphs resulting from decompilation.

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- Shortsighted Data Flow Graphs (SDFG) - each obtained by merging all paths through the AST corresponding to a constituent function

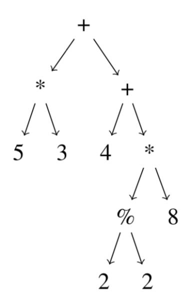
Abstract Syntax Trees

Example: Arithmetic Expressions

Consider the following BinaryOp expression:

$$5 * 3 + (4 + 2 \ \% \ 2 * 8)$$

The semantic structure of this expression can be distilled by considering the following binary tree:



Distilled semantic structure = order of operations

CLR AST Dictionary - CLR-Specific or C#-specific AST Members in Blue

Control Flow

- if - reference the conditional and execute accordingly
- break - immediately exit the enclosing loop
- CLRWhile - infinite loop

Expressions

Code that when evaluated **does** yield a value. Valid in places such as tests, for loops, conditionals, or as the right-hand side of assignments.

- BinaryOp - expression computed from two operands and some operator
- Call - function call, including list of args pass to the function

Statements

Code that when evaluated **does not** yield a value. E.g., a statement cannot be on the right-hand side of an assignment.

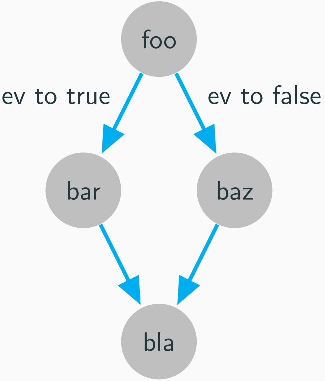
- Assignment - storage of rh variable to the location yielded by lh variable
- CLRVariableWithInitializer - declaration and subsequent initialization

CLR-Specific or C#-specific AST Members

Construction of Shortsighted Data Flow Graph

Small code block resulting in a nonlinear SDFG.

```
if foo() {
        bar();
}
else {
        baz();
}
bla();
```



Functions on SDFG Graphs - Motivation

We often study an object X by studying a set of functions defined on X

$$X^* := \{f : X \longrightarrow \mathbb{R}\}$$

Example 1

Consider the case of a distribution $\mathcal{D}$ on a sample space Ω defined by the measure μ. We might choose to study $\mathcal{D}$ by studying

$$f_n : \mathcal{D} \mapsto \int_\Omega x^n d\mu(x)$$

Example 2

Consider the set of invertible $n \times n$ matrices $GL_n(\mathbb{F})$ on some field $\mathbb{F}$. We might choose to study $GL_n(\mathbb{F})$ by studying

$$\mathrm{tr}, \det : GL_n(\mathbb{F}) \longrightarrow \mathbb{R}$$

Functions on SDFG Graphs

Let G be a SDFG graph resulting from traversing a given AST corresponding to some source code function.

Example

Define

$$\text{NumPass2Call} : \mathrm{Vert}(G) \longrightarrow \mathbb{R}$$

by

$$v \mapsto \#\text{args}_v$$

where $\#\text{args}_v$ is the number of arguments passed to the function called at v.

Other Examples:

1. $\text{BinaryOp} : v \mapsto \eta(\text{whichOpCode}_v)$

for some string-to-float hash function η.

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Other Examples:

1. $\text{BinaryOp} : v \mapsto \eta(\text{whichOpCode}_v)$
2. $\text{CLRClassRef} : v \mapsto \eta(\text{ReferencedClass}_v)$

for some string-to-float hash function η.

Graph Antiderivative - Ingredients

In order to define an integral of a function

$$f : \mathrm{Vert}(G) \longrightarrow \mathbb{R}$$

for G a directed graph, we must define a measure μ on $\mathrm{Vert}(G)$ in such a way that f is measurable.

We do this by imposing a Markov chain structure on G and taking μ to be the PageRank measure

$$\mathbb{P} : \mathrm{Vert}(G) \longrightarrow [0, 1]$$

$$v \mapsto \mathrm{PageRank}(G)_v$$

where the PageRank vector is taken to be the steady-state probability distribution over the nodes resulting from the long-run behavior of the random-walk Markov Chain.

Graph Integration

Markov Chains and the PageRank Vector

Definition

A discrete-time *Markov chain* is a sequence of random variables $X_1, X_2, \ldots$ such that

$$P(X_{n+1} = x | X_1 = x_1, \ldots, X_n = x_n) = P(X_{n+1} = x | X_n = x_n)$$

Given G, order the vertices $\{v_i\}$ of the graph G and define the $n \times n$ probability transition matrix T by

$$t_{ij} = \begin{cases} 1/|v_i^{\text{out}}| & \textit{if } (v_i, v_j) \in \mathrm{Edges}(G) \\ 0 & \text{otherwise} \end{cases}$$

where v_i^{out} is the set of edges emanating from vertex v_i and $n = |\mathrm{Vert}(G)|$.

To ensure the irreducibility of our transition matrix, we smooth T to

$$M = (1-p)T + pB \qquad \text{(Perron-Frobenius)}$$

where

$$B = \frac{1}{n} \begin{bmatrix} 1 & 1 & \ldots \\ \vdots & \ddots & \\ 1 & & 1 \end{bmatrix}$$

PageRank Measure

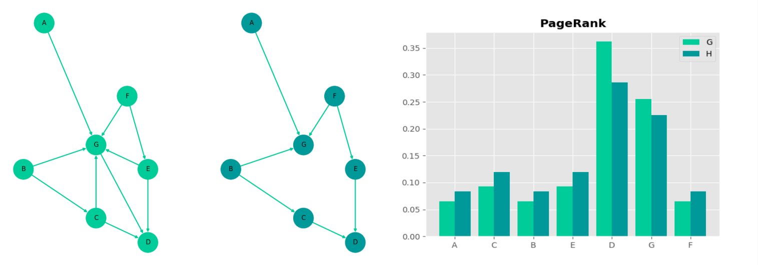
The PageRank vector $\mathbb{P}$ is given by the left eigenvector of M and corresponds to

$$\lim_{n\to\infty} M^n \frac{1}{|\mathrm{Vert}(G)|} \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix}$$

and can usually be adequately approximated with $n = 10$.

The corresponding Markov chain is defined by

$$P(X_t = v_i | X_{t-1} = v_j) = (1-p)t_{ij} + p\frac{1}{n}$$



Construction of the Graph Integral

Consider a function $f : \mathrm{Vert}(G) \longrightarrow \mathbb{R}$ for G a finite directed graph.

Let $\mathbb{P} = \{p_v\}$ be the PageRank measure on $\mathrm{Vert}(G)$. We can then define a measure ν_f on $\mathrm{Vert}(G)$ by

$$\begin{aligned}\nu_f(S) &= \int_S f \, d\mathbb{P} \\ &= \sum_{\alpha_j \in \mathrm{image}(f)} \alpha_j \mathbb{P}(f^{-1}(\alpha_j) \cap S) \\ &= \sum_{v \in S} f(v) p_v\end{aligned}$$

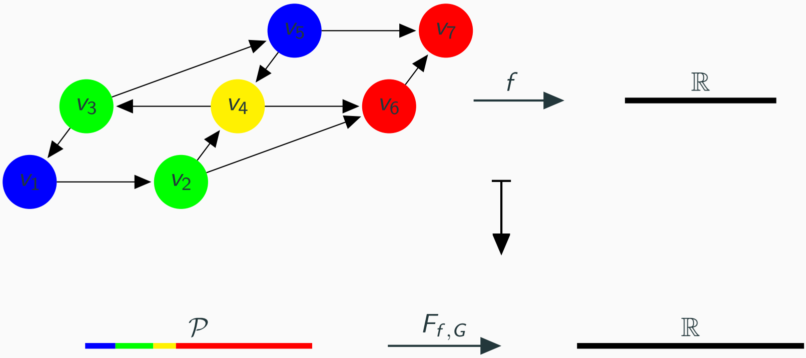
Let $\mathcal{P}$ be a partition of $[0,1]$ and let $G_q = \{v | p_v \leq q\}$.

$$G_{q_1} \subseteq G_{q_2} \subseteq \cdots \subseteq G_{q_{|\mathcal{P}|}} = \mathrm{Vert}(G)$$

allows us to define our graph antiderivative $F_{f,G}$ of f by

$$\begin{aligned}F_{f,G} &:= (\nu_f(G_{q_1}), \nu_f(G_{q_2}), \ldots, \nu_f(G_{q_{|\mathcal{P}|}})) \\ &= (\mathbb{E}[f|_{G_{q_1}}], \mathbb{E}[f|_{G_{q_2}}], \ldots, \mathbb{E}[f|_{G_{|\mathcal{P}|}}])\end{aligned}$$

The Graph Antiderivative Visualized



Antiderivative

$$\Gamma \times \mathrm{Fun}(\bigsqcup_{\Gamma} \mathrm{Vert}(G), \mathbb{R}) \longrightarrow \mathrm{Fun}(\mathcal{P}, \mathbb{R})$$

$$(G, f) \mapsto (F_{f,G} : q \mapsto \mathbb{E}[f|_{G_q}]),$$

Graph Integration: Example

Consider a SDFG G given by:

$$\mathrm{Edge}(G) = \{(v_1, v_2), (v_1, v_3), (v_2, v_4), (v_3, v_4)\}$$

$$\mathsf{PageRank}(G) = \langle p_{v_1} = 0.10, p_{v_2} = 0.15, p_{v_3} = 0.25, p_{v_4} = 0.50\rangle$$

Assume the nodes $v_1, v_4 \in \mathrm{Vert}(G)$ both correspond to function calls $\phi_{v_i}(args_{v_i})$, where $args_{v_i}$ represent the set of arguments passed to ϕ_{v_i}. Define

$$\mathsf{NumPass2Call} : \mathsf{Vert}(G) \longrightarrow \mathbb{R}$$

by

$$v_i \mapsto \begin{cases} \#\mathsf{args}_{v_i} & \text{if } i \in \{1, 4\} \\ 0 & \text{otherwise} \end{cases}$$

Let $\mathcal{P} = (0.05, 0.12, 0.95)$.

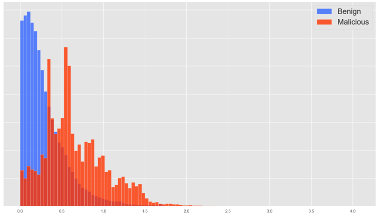
Then $F_{\mathrm{NumPass2Call},G} : \mathcal{P} \longrightarrow \mathbb{R}$ takes the form

$$\begin{pmatrix} 0.05 \\ 0.12 \\ 0.95 \end{pmatrix} \mapsto \begin{pmatrix} 0 \\ 0.1 * \#\mathsf{args}_{v_1} \\ 0.1 * \#\mathsf{args}_{v_1} + 0.5 * \#\mathsf{args}_{v_4} \end{pmatrix}$$

Results

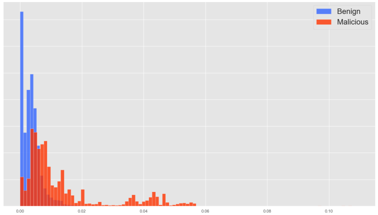
Vectorization Efficacy

$\int_0^{0.6}$ ClassRefname : $v \mapsto \eta(\text{name}(v))d\mathbb{P}$



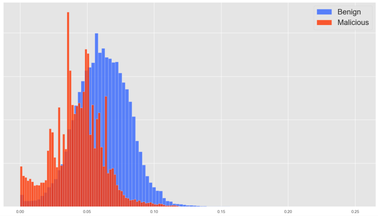
Name of referenced class at v

$\int_0^{0.4}$ CLRLiteral : $v \mapsto \eta(\text{type}(v))d\mathbb{P}$



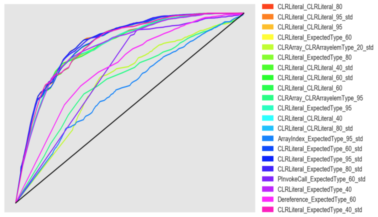
Type of literal occurring at v

$\int_0^{0.95}$ ArgRefType : $v \mapsto \eta(\text{type}(v))d\mathbb{P}$



Type of argument referenced at v

Top Features by AUC



Value/type of literal expression at v

Model Results - Random Forest

Table 1: Graph Antiderivative-based vectorization

Class	Precision	Recall	F1-score	Support
Benign	97.88%	99.37%	98.62%	696827
Malware	98.94%	96.47%	97.69%	424420
avg/total	98.28%	98.27%	98.27%	1121247
False Positive Rate	1.10%			
False Negative Rate	1.72%			

Table 2: Text-only vectorization

Class	Precision	Recall	F1-score	Support
Benign	90.61%	87.04%	88.79%	696827
Malware	87.80%	91.18%	89.46%	424420
avg/total	89.19%	89.13%	89.13%	1121247
False Positive Rate	8.79%			
False Negative Rate	12.96%			

Questions?