Applications of Graph Integration to Function Comparison and Malware Classification

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Cylance Inc.

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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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)

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

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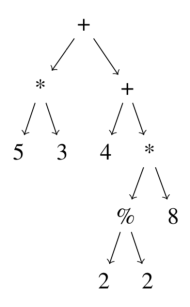

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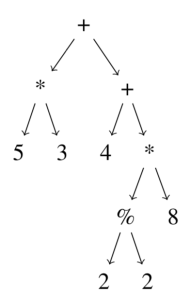

Distilled semantic structure = order of operations

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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

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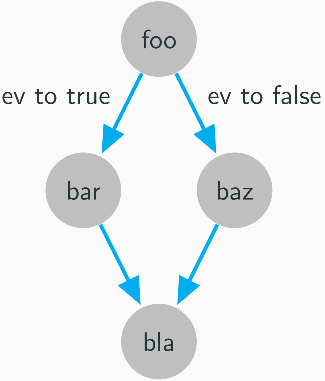

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Example 2

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

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

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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

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

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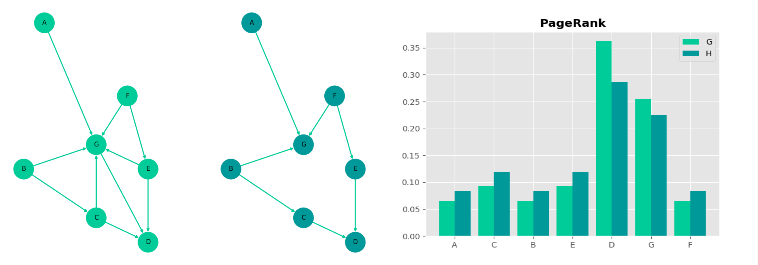

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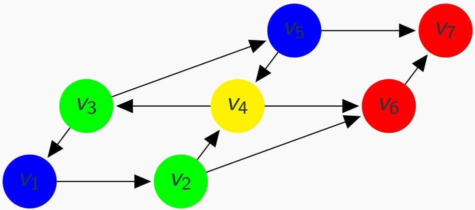

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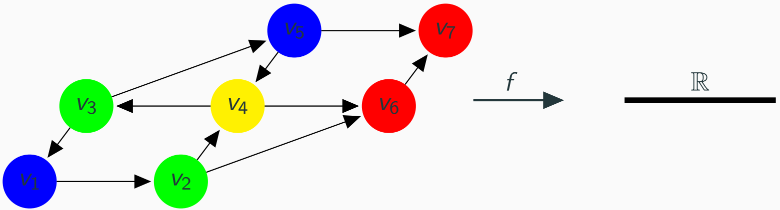

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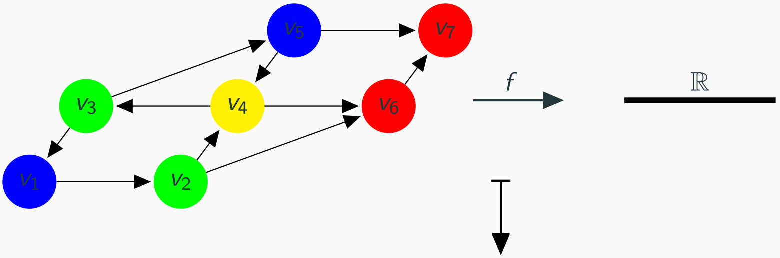

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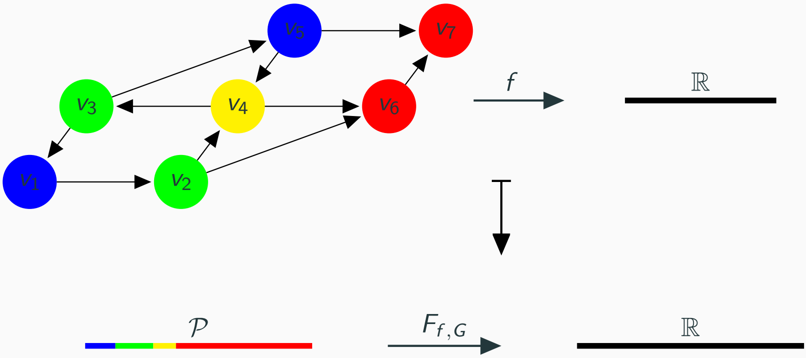

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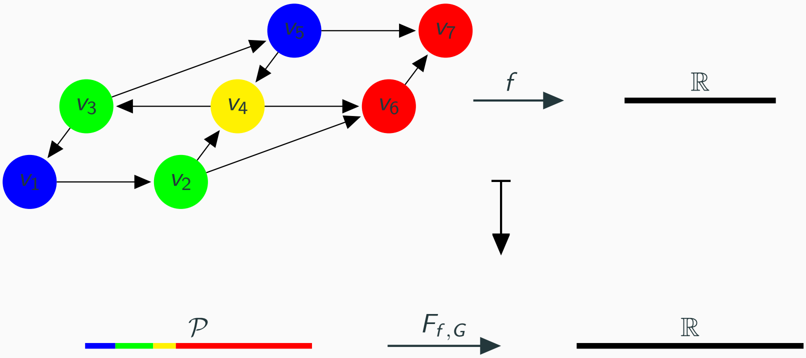

Antiderivative

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

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

Graph Integration: Example

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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

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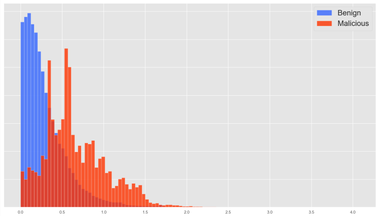
$\int_0^{0.6} \mathrm{ClassRefname} : v \mapsto \eta(\mathrm{name}(v))d\mathbb{P}$



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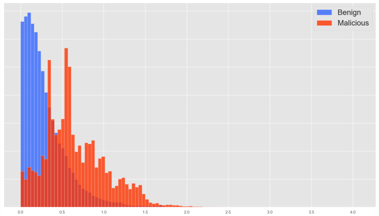

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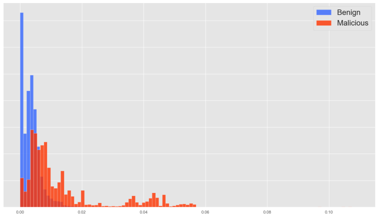
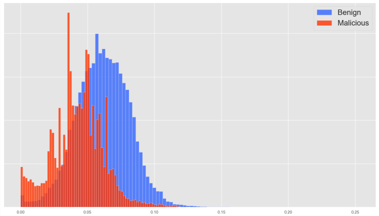
$\int_0^{0.4} \text{CLRLiteral} : v \mapsto \eta(\text{type}(v))d\mathbb{P}$



Type of literal occurring at v

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



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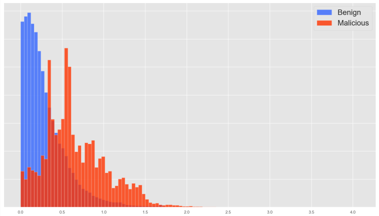

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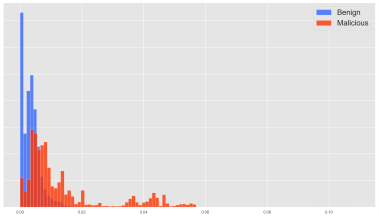

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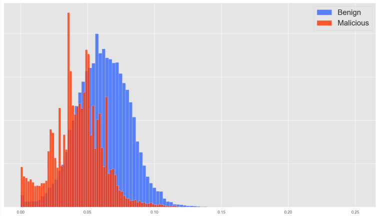
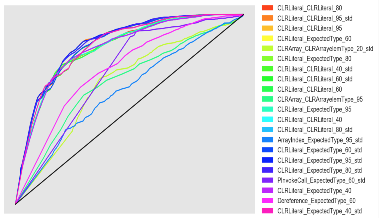
$\int_0^{0.95} \text{ArgRefType} : v \mapsto \eta(\text{type}(v))d\mathbb{P}$



Type of argument referenced at v

Top Features by AUC



Value/type of literal expression at v

Model Results - Random Forest

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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%			
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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?