Early WCET Prediction using Machine Learning (Work in Progress)

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Preliminary Results

Conclusion

Cost of a Bug

Relative cost of a bug (according to IBM)

Design phase	1
After development	5
After deployment	100

'The cost to fix an error found after product release was four to five times as much as one uncovered during design, and up to 100 times more than one identified in the maintenance phase.'

- IBM Systems Sciences Institute

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Cost of a Bug

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\rightarrow Transfer to WCET?



Conclusion

What the Industry Wants



Conclusion

What the Industry Wants



 \rightarrow Realistic expectations?

'This is a very wild idea and I doubt that it will work on real programs.'

- An anonymous reviewer

Preliminary Results Preview

Tachniqua	Accuracy				
Technique	Training set	Evaluation set			
Multi Lavor Porcontron	Err. 10%	Err. 11%			
Multi-Layer Perceptron	24% и. 0% о.	24% u. 1% o.			
Random Forest	Err. 4%	Err. 12%			
Random Forest	3% и. 0% о.	4% и. 2% о.			
Linear Regression		Err. 10%			
		8% u. 4% o.			

 $\rightarrow\,$ So far the results on TACLeBench are partial and disappointing

These results are due to Frédéric Fort.

Our Proposal: Use Machine Learning

Machine Learning Input: a Spreadsheet					
Program	Characteristic 1	Characteristic 2		WCET	
А				1410	
В				6912	
:					



Machine Learning Output: a Formula

WCET \simeq *f*(characteristics)

Source Code Analysis

Preliminary Results

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Outline of the Presentation



- **2** Learning Framework
- **3** Source Code Analysis
- **4** Preliminary Results

Source Code Analysis

Preliminary Results

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Learning Framework



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Issue 1/3: The Learning Set



Machine Learning requires:

- Large sets (more than 1000 programs)
- Representative sets

Candidates program sets

- Benchmarks
- Industrial bank of functions
- Generated programs

repr. ok, size not ok

good repr., borderline size, availability issue

unlimited size, doubtful repr., compilation optim. issue

Source Code Analysis

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Issue 2/3: The Characteristics

Choose



Gather

	C1	C2	 WCET
Α			
В			

Machine Learning requires:

- Numerical or discrete characteristics
- Characteristics controlling the learnt attribute

 $\, \hookrightarrow \, \, {\sf Syntactic \ characteristics \ are \ insufficient}$

We rely on worst-case numerical metrics (details follow shortly)

Source Code Analysis

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Issue 3/3: Feasibility and Validation

Do it exists a set of characteristics of the source code controlling the WCET?

 $\rightarrow\,$ We consider prediction in $\pm 20\%$ as OK



Conclusion

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	C1	C2	 WCET
A	230	45	
в			

Worst Case Event Count Analysis

The worst case event count analysis delivers an over-approximation of the number of events by category triggered by any symbolic execution of the source program.

• Example of categories:

- Reading a variable
- Performing a non-trivial multiplication
- "Branching" back to the loop head
- A mapping from category to number is called a "metric"

Playing with Metrics

- Sequential code gives one metric
- Alternatives should be combined with care
 - $m_1 \sqcup m_2$ is a sound but coarse approximation of " m_1 or m_2 "

$$\begin{bmatrix} Addition \mapsto 3\\ Product \mapsto 4 \end{bmatrix} \sqcup \begin{bmatrix} Addition \mapsto 4\\ Division \mapsto 2 \end{bmatrix} = \begin{bmatrix} Addition \mapsto 4\\ Product \mapsto 4\\ Division \mapsto 2 \end{bmatrix}$$

- If neither $m_1 \prec m_2$ nor $m_2 \prec m_1$ we continue with $\{m_1, m_2\}$
 - The analysis is disjunctive (complexity issue)
 - $\bullet~$ Using bounds on the categories costs, we strengthen the \prec relation

$$\begin{bmatrix} Jump \mapsto 11 \\ Addition \mapsto 2 \end{bmatrix} \prec \begin{bmatrix} Jump \mapsto 14 \\ Product \mapsto 5 \end{bmatrix}$$

- Loop bounds are needed
- Eventually \bigsqcup is used to get a unique metric

Categories retained (so far)

Our implementation of the analysis considers:

Family	Category	Optimistic	Pessimistic
	Simple	0.5	1
Operations	Multiplication	1	5
	Division	1	10
	Unconditional branch	0.5	1
Cartal	Conditional branch	1	1
Control	Computed branch	1	4
	Call	0.5	10
	Address setting	0.5	1
Memory	Load	2	20
	Store	2	20

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Experiments Setting

• Programs are compiled with gcc

 $\, \hookrightarrow \, \, \text{The target is ARM}$

- Worst Case Event Count analysis is performed by oRange
- WCET analysis is performed by OTAWA

 $\,\hookrightarrow\,$ The model is a simple ARMv5

Preliminary Results

Conclusion

Program Sets Involved

- Training set (10000)
 - $\,\hookrightarrow\,$ Generated randomly (with if and for statements)
- Evaluation set (5000)
 - $\,\hookrightarrow\,$ Generated the same way
- TACLeBench (23)
 - $\,\hookrightarrow\,$ Sequential part of the benchmark

Preliminary Results

Conclusion

Learning Techniques Explored

- Multi-Layer Perceptron
 - $\, \hookrightarrow \, \, \mathsf{State-of-the-art} \, \, \mathsf{neural} \, \, \mathsf{network} \,$
- Random Forest
 - $\, \hookrightarrow \, \, {\sf Huge \ decision \ tree}$
- Linear Regression
 - $\,\hookrightarrow\,$ Best linear combination of the characteristics

(Preliminary Results)

Conclusion

Accuracy Evaluation

• Applying the learnt formula on a set of programs gives statistics

Correlation coefficient	0.9961
Mean absolute error	187.9878
Root mean squared error	490.4514
Relative absolute error	4.2395
Root relative squared error	8.972
Total Number of Instances	10000
Underestimations	283
Overestimations	0

• We make the following summaries:

Err.	4%
<mark>3</mark> % и.	0% o.

Conclusion

Current Accuracy of our Approach

Technique Accurate Training set		асу			
		Evaluation set			
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(Preliminary Results)

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Linear Regression Formula

WCET =	0.0506	*	SimpleOp
+	2.2557	*	Mult
+	0	*	Div
+	1.0391	*	CondBr
+	2.638	*	UncondBr
+	0	*	CalcBr
+	0	*	Call
+	0	*	Return
+	1.9445	*	Address
+	0	*	Load
+	0	*	Store
+	18.4446		

Related Work

Gustafsson et al.^{1,2} follow the same objective with different tools

• Measurement-based approach

 $\,\hookrightarrow\,$ No need for hardware model but need the hardware itself

- Ad-hoc learning techniques
- Evaluation on the Mälardalen benchmark gives:

• ,	Accurate approach:		Err. 8%		
			4% и. 9% о.		9% o.
· Pessimistic approac			Er	r.	31%
•	ressimistic approach.		0% u		52% o.

¹Jan Gustafsson et al. "Approximate Worst-Case Execution Time Analysis for Early Stage Embedded Systems Development". In: **SEUS**. 2009.

²Peter Altenbernd et al. "Early execution time-estimation through automatically generated timing models". In: **Real-Time Systems** (2016).

Preliminary Results



Conclusion

Work in Progress

- We seek early WCET predictions through Machine Learning
- We proposed a source analysis for retrieving program metrics

 $\,\hookrightarrow\,$ Required for both learning and predicting

- Several question are opened
 - Relevant characteristics
 - Best learning technique

