Automatic Resource Bound Analysis and Linear Optimization

Jan Hoffmann

Carnegie Mellon

## Beyond worst-case analysis

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... of algorithms

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... of algorithms

## Resource bound analysis

## Beyond worst-case analysis

... of algorithms

Resource bound analysis
... of programs / software

Motivation: Why analyze resource usage of programs?

## Resource Usage in Safety-Critical Systems

Memory Usage

Timing

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Memory Usage

Timing

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Toyota's killer firmware: Bad design and its consequences
Michael Dunn -October 28, 2013
109 Comments

On Thursday October 24, 2013, an Oklahoma court ruled against Toyota in a case of unintended acceleration that lead to the death of one the occupants. Central to the trial was the Engine
Control Module's (ECM) firmware.
Unintended acceleration in
Toyota cars in the US 2005-2009.

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Timing


ICE 3 Velaro D delivery delayed by one year because of software performance issues in 2013.

## Performance Bugs are Common and Expensive



The System is down at the moment.
We're working to resolve the issue as soon as possible. Please try again later.

Please include the reference ID below if you wish to contact us at 1-800-318-2596 Error from: https\%3A//www.healthcare.gov/marketplace/global/en_US/registration\% Reference ID: 0.cdc7c117.1380633115.2739dce8

HealthCare.gov debacle has been mainly caused by performance issues.

# Google Apps 

Google Apps Developer:
"Cannot test for performance bugs with regression test".

## Software Security



Algorithmic Complexity Attacks


Side-Channel Attacks

## Software Security



Algorithmic Complexity Attacks


Side-Channel Attacks

Space/Time Analysis for Cybersecurity (STAC)
October 2014
\$ 53M program

Our team:
GRAMMATECH
Carnegie Mellon
Yale wisconsin

## Static Resource Bound Analysis

Given: A program P

Question: What is the worst-case resource consumption of $P$ as a function of the size of its inputs?

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## Automatic

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Static Resource Bound Analysis

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## Research Challenges

Model and predict resource usage at development time.


Source code

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Model and predict resource usage at development time.


## Research Challenges

Help developers to reason about quantitative properties.

- Computer support: Modeling, specification, verification, automation and user interaction
- Compositionally: Track size changes and specify resource-usage of library code
- Language features: Concurrency, higher-order, data structures, ...


## Why is this Related?

1. Beyond worst-case analysis of algorithms

- Automation
- Concrete (non-asymptotic) bounds for specific hardware

2. We face similar challenges in resource-bound analysis

- "The worst-case behavior doesn't happen in practice."

3. We reduce bound inference to linear optimization

- Linear programs we get are solvable in linear time in practice
- Theoretical worst-case of the algorithm is exponential (simplex)


## Outline

- Motivation
- How does automatic resource bound analysis work?
- How well does automatic resource bound analysis work? (implementation and experiments)
- What are the properties of the LP instances that we get?


Bird's Eye View
Type-Based Resource Analysis


## Bird's Eye View





Run-time system
Hardware


## Bird's Eye View



|  | $12 n^{2}+14 n+3$ |
| :---: | :---: |
| Resource Bound |  |



Bird's Eye View


Run-time system
Hardware

| $12 n^{2}+14 n+3$ <br> Resource Bound | applies to | Machine Code |
| :---: | :---: | :---: |

## Bird's Eye View




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Bird's Eye View


## Bird's Eye View

## Idea: Automate Amortized Analysis

- Assign potential functions to data structures
$\Rightarrow$ States are mapped to non-negative numbers

$$
\Phi(\text { state }) \geq 0
$$

- Potential pays the resource consumption and the potential at the following program point

$$
\Phi(\text { before }) \geq \Phi(\text { after })+\text { cost }
$$

$\downarrow$ telescoping $\downarrow$

- Initial potential is an upper bound
$\Phi($ initial state $) \geq \sum \operatorname{cost}$


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\downarrow \text { telescoping } \downarrow \\
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- Initial potential is an upper bound

Type systems for automatic analysis

- Fix a format of potential functions
- Develop type rules that manipulate potential functions


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- Develop type rules that manipulate potential functions


## Example: Append for Persistent Lists

append $(x, y)$
Heap-space usage is 2 n if

- n is the length of list x
- One list element requires two heap cells (data and pointer)


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## Example: Append for Persistent Lists

## append( $x, y$ )

Heap-space usage is 2 n if

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Example evaluation:



Heap usage: $2^{*} n=2 * 3=6$

## Example: Composing Calls of Append

```
f(x,y,z) = {
    t = append(x,y);
    append(t,z)
}
```

Heap usage of $f(x, y, z)$ is $2 n+2(n+m)$ if

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## append(t,z)

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$z \rightarrow$ f. (e)- d. (c). (a) append $(t, z)$

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Implicit reasoning about size-changes.

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Example: Composing Calls of Append

$$
\begin{aligned}
& f(x, y, z)=\left\{\text { append: }\left(L^{4}(i n t), L^{2}(i n t)\right)-\theta / 0\right\rangle L^{2} \text { (int) } \\
& t=\text { append }(x, y) ; \\
& \text { append }(t, z) \\
& \} \quad \text { append: }\left(L^{2}(i n t), L^{0}(i n t)\right)-0 / 0\right\rangle L^{0}(\text { int })
\end{aligned}
$$

The most general type of append is specialized at call-sites:

$$
\text { append: }\left(L^{q} \text { (int), } L^{p} \text { (int)) }-\frac{s}{-}-\underline{L} L^{r} \text { (int) } \mid \Phi\right.
$$

## Polynomial Potential Functions

## Linear Potential

## Functions

User-defined resource metrics
(i.e., by tick(q) in the code)

Naturally compositional: tracks size changes, types are specifications

Bound inference by reduction to efficient LP solving

Type derivations prove bounds with respect to the cost semantics

## Phd Thesis: Polynomial Potential Functions

## Linear Potential Multivariate Polynomial

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## For example $\mathrm{m}^{\star} \mathrm{n}^{2}$.

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# Phd Thesis: Polynomial Potential Functions 

First automatic, type-based resource analysis for polynomial bounds.

## Example: Polynomial Potential Functions

$t=$ append (xs,ys); quicksort( $t$ )

Computed time bound:
$12 m^{2}+24 m n+12 n^{2}+14 m+22 n+11$

## Example: Polynomial Potential Functions

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append: $\left((L(i n t), L(i n t)),\left(\begin{array}{ccc}6 & 26 & 24 \\ 34 & 24 \\ 24\end{array}\right)\right) \rightarrow(L(i n t),(3,26,24))$
quicksort: $(L(i n t),(3,26,24)) \rightarrow(L(i n t),(0,0,0))$

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quicksort : $(L($ int $),(3,26,24)) \rightarrow(L(i n t),(0,0,0))$

## Multivariate Resource Polynomials [POPL'11]

Map data structures to non-negative rational numbers $p: \llbracket A \rrbracket \rightarrow \mathbb{Q}_{0}^{+}$

Are non-negative linear combinations of the following base polynomials:

$$
\begin{aligned}
& \mathcal{P}(\text { Int })=\{a \mapsto 1\} \\
& \mathcal{P}\left(A_{1}, A_{2}\right)=\left\{\left(a_{1}, a_{2}\right) \mapsto p_{1}\left(a_{1}\right) \cdot p_{2}\left(a_{2}\right) \mid p_{i} \in \mathcal{P}\left(A_{i}\right)\right\} \\
& \mathcal{P}(L(A))=\left\{\left[a_{1}, \ldots, a_{n}\right] \mapsto \sum_{1 \leq j_{1}<\cdots<j_{k} \leq n} \prod_{i=1}^{k} p_{i}\left(a_{j_{i}}\right) \mid k \in \mathbb{N}, p_{i} \in \mathcal{P}(A)\right\}
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\text { Important innovation: } \\
\text { sigma-pi formula for data } \\
\text { structures }
\end{array}\right.\right. \\
& \mathcal{P}(L(A))=\left\{\left[a_{1}, \ldots, a_{n}\right] \mapsto \sum_{1 \leq j_{1}<\cdots<j_{k} \leq n} \prod_{i=1}^{k} p_{i}\left(a_{j_{i}}\right) \mid k \in \mathbb{N}, p_{i} \in \mathcal{P}(A)\right\}
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$$

## Resource Polynomials: Examples

$$
\mathcal{P}(L(A))=\left\{\left[a_{1}, \ldots, a_{n}\right] \underset{1 \leq i \leq i}{\leftrightarrow} \sum_{\mathcal{U}_{i} \leq n} \prod_{i=1}^{k} p_{i}\left(a_{j i}\right) \mid k \in \mathbb{N}, p_{i} \in \mathcal{P}(A)\right\}
$$

## Resource Polynomials: Examples

$$
\left[a_{1}, \ldots, a_{n}\right] \mapsto 8 n+3
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## Resource Polynomials: Examples

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\begin{aligned}
& {\left[a_{1}, \ldots, a_{n}\right] \mapsto 8 n+3} \\
& {\left[a_{1}, \ldots, a_{n}\right] \mapsto 36\binom{n}{3}+16\binom{n}{2}+20 n+3}
\end{aligned}
$$

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& \left(\left[a_{1}, \ldots, a_{n}\right],\left[b_{1}, \ldots, b_{m}\right]\right) \mapsto 39 m n+6 m+21 n+19
\end{aligned}
$$

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& \left(\left[a_{1}, \ldots, a_{n}\right],\left[b_{1}, \ldots, b_{m}\right]\right) \mapsto 39 m n+6 m+21 n+19 \\
& {\left[\left[a_{1}^{1}, \ldots, a_{m_{1}}^{1}\right], \ldots,\left[a_{1}^{n}, \ldots a_{m_{n}}^{n}\right]\right] \mapsto 18\binom{n}{2}+12 n+3+\sum_{1 \leq i<j \leq n} 12 m_{i}} \\
& \mathcal{P}(L(A))=\left\{\left[a_{1}, \ldots, a_{n}\right] \mapsto \sum_{1 \leq j_{1}<\cdots<j_{k} \leq n} \prod_{i=1}^{k} p_{i}\left(a_{j_{i}}\right) \mid k \in \mathbb{N}, p_{i} \in \mathcal{P}(A)\right\}
\end{aligned}
$$

## Automatic Computation of the Bounds

1. Fix a maximal degree of resource polynomials
2. Annotate each type with (yet unknown) coefficients for resource polynomials

Example for degree 2: $\left((L(i n t), L(i n t)), q_{0,0}, q_{1,0}, q_{2,0}, q_{1,1}, q_{0,1}, q_{0,2}\right)$

General case: index system that enumerates resource polynomials
3. Extract linear constraints for the coefficients during type inference
4. Solve the constraints with an LP solver

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$$
q_{0,0}+q_{1,1} n m+q_{1,0} n+q_{2,0}\binom{n}{2}+q_{0,1} m+q_{0,2}\binom{m}{2}
$$

Example for degree 2: $\left((L(i n t), L(i n t)), q_{0,0}, q_{1,0}, q_{2,0}, q_{1,1}, q_{0,1}, q_{0,2}\right)$

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- How does automatic resource bound analysis work?
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- What are the properties of the LP instances that we get?


## Resource Aware ML

- Based on Inria's OCaml compiler
- ~12,000 lines of code (+ ~29,000 loc form the OCaml compiler)
- Currently we use Coin-Or's CLP C interface
- Features:
- Higher-order functions and polymorphism
- User defined inductive types
- Parallel evaluation
- Side effects
- User defined (non-monotone) resource metrics
- Upper and lower bounds


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## Web interface at http://raml.co

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Experimental Evaluation

| Quick Sort (Integers) | $12 \mathrm{n}^{2}+14 \mathrm{n}+3$ | $\mathrm{O}\left(\mathrm{n}^{2}\right)$ | 0.1 s |
| :--- | :--- | :--- | :--- |
| Split and Sort | $16 \mathrm{n}^{2}+46 \mathrm{n}+9$ | $\mathrm{O}\left(\mathrm{n}^{2}\right)$ | 2.1 s |
| Insertion Sort (Strings) | $8 \mathrm{n}^{2} \mathrm{~m}+8 \mathrm{n}^{2}-8 \mathrm{~nm}+4 \mathrm{n}+3$ | $\mathrm{O}\left(\mathrm{n}^{2} \mathrm{~m}\right)$ | 0.91 s |
| Duplicate Elimination | $6 \mathrm{n}^{2} \mathrm{~m}+9 \mathrm{n}^{2}-6 \mathrm{~nm}+3 \mathrm{n}+3$ | $\mathrm{O}\left(\mathrm{n}^{2} \mathrm{~m}\right)$ | 0.97 s |
| Longest Common <br> Subsequence | $39 \mathrm{~nm}+6 \mathrm{~m}+21 \mathrm{n}+19$ | $\mathrm{O}(\mathrm{nm})$ | 0.36 s |
| Matrix Multiplication | $28 \mathrm{xmn}+32 \mathrm{xm}+2 \mathrm{x}+14 \mathrm{n}+21$ | $\mathrm{O}(\mathrm{xmn})$ | 1.96 s |
| Breadth-First Matrix <br> Multiplication | $2 \mathrm{yz}+15 \mathrm{ynmx}+14 \mathrm{ynm}+15 \mathrm{yn}+104 \mathrm{n}+51$ | $\mathrm{O}(\mathrm{ynmx})$ | 4.98 s |
| Dijkstra's Shortest-Path <br> Algorithm | $79.5 \mathrm{n}^{2}+31.5 \mathrm{n}+38$ | $\mathrm{O}\left(\mathrm{n}^{2}\right)$ | 2.50 s |
| In-Place Quick Sort for <br> Arrays | $12.25 x^{2}+52.75 \mathrm{x}+3$ | $\mathrm{O}\left(\mathrm{x}^{2}\right)$ | 0.64 s |

## Micro Benchmarks



Quick Sort for Integers
Evaluation-step bound vs. measured behavior


Quick Sort for Integers
Evaluation-step bound vs. measured behavior
measured worst-case steps

$$
39 x y+6 y+21 x+19
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Longest Common Subsequence

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Longest Common Subsequence

Evaluation-step bound vs. measured behavior

```
measured worst-case steps
8xxy + 8xx - 8xy + 4x + 3
```



Insertion Sort for Strings

Evaluation-step bound vs. measured behavior

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measured worst-case steps
8xxy + 8xx - 8xy + 4x + 3
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Insertion Sort for Strings

Evaluation-step bound vs. measured behavior

## Macro Benchmarks

1) OCaml's standard list library list.ml

- Evaluation-step bounds for 47 of 51 top-level functions
- 428 lines of code; 3.2 seconds on a Macbook Pro


## 2) CompCert C Compiler

- OCaml code extracted from the Coq specification
- Evaluation-step bounds for 13 topmost modules in the dependency graph
- 138 of 164 functions bounded; 2740 lines of code; 21min


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- OCaml code extracted from the Coq specification
- Evaluation-step bounds for 13 topmost modules in the dependency graph

Problems: Modules and untyped code.

- 138 of 164 functions bounded; 2740 lines of code; 21 min

| Metric | \#Funs | LOC | Time | \#Const | \#Lin | \#Quad | \#Cubic | \#Poly | \#Fail | Asym. <br> Tight |
| :---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: |
| steps | 243 | 3218 | 72.10 s | 16 | 130 | 60 | 28 | 239 | 4 | 225 |
| heap | 243 | 3218 | 70.36 s | 41 | 112 | 60 | 22 | 239 | 4 | 225 |
| tick | 174 | 2144 | 64.68 s | 19 | 79 | 53 | 19 | 174 | 0 | 160 |
| CompCert: |  |  |  |  |  |  |  |  |  |  |
| steps | 164 | 2740 | 1300.91 s | 32 | 99 | 7 | 0 | 138 | 26 | 137 |

## Macro Benchmarks

How can we make predictions about compiled code?

## Machine Learning Cost Models

How to obtain realistic cost metrics for high-level analysis?

- Treat hardware, compiler, and runtime systems as black box
- Select training programs that cover relevant operations
- Use linear regression to obtain average time and memory costs of operations
- Combine time and memory predictions to get a time model for execution with garbage collection


## Bound for List Append on x86

### 1.6 GHz Intel Core i5-5250U processor



## Outline

- Motivation
- How does automatic resource bound analysis work?
- How well does automatic resource bound analysis work? (Implementation and experiments)
- What are the properties of the LP instances that we get?


## Network-Flow Problems

Constraints we derive are almost network-flow problems

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Network-flow constraints:

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Inflow.


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Network-flow constraints:
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Inflow.


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Flow capacity.

## Linear Constraints have a Simple Form

- Pay for constant cost

$$
q=q^{\prime}+c
$$

- Account for size changes

$$
q_{i}^{\prime}=q_{i}+q_{i+1}
$$

- Recursive call

$$
q=p
$$

- Conditional branches

$$
q \geq p_{1} \quad q \geq p_{2}
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q \geq p_{1} \quad q \geq p_{2}
$$

Cover cost in both branches (possible waste).

## Accounting for Size Change

List types: $\quad L^{\left(q_{1}, \ldots, q_{k}\right)}(A)$
Potential: $\quad \Phi\left(\ell: L^{\left(q_{1}, \ldots, q_{k}\right)}\right)=\sum_{i=1, \ldots, k} q_{i}\binom{|\ell|}{i}$
Additive shift: $\triangleleft\left(q_{1}, \ldots, q_{k}\right)=\left(q_{1}+q_{2}, \ldots, q_{k-1}+q_{k}, q_{k}\right)$

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\sum_{i=1, \ldots, k} q_{i}\binom{n+1}{i}=q_{1}+\sum_{i=1, \ldots, k-1} q_{i+1}\binom{n}{i}+\sum_{i=1, \ldots, k} q_{i}\binom{n}{i}
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## potential of a list

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## Generation of Linear Constraints

1. It is easy to pass potential to list tails without loss

$$
\Phi\left((x:: x s): L^{\vec{q}}\right)+c=\Phi\left(x s: L^{\triangleleft(\vec{q})}\right)+\left(q_{1}+c\right)
$$

2. Pattern: one recursive call and polynomial spill

$$
\Phi\left((x:: x s): L^{\vec{q}}\right)-\Phi\left(x s: L^{\vec{q}}\right)=\Phi\left(x s: L^{\left(q_{2}, \ldots, q_{k}, 0\right)}\right)+q_{1}
$$

3. It is easy to share potential when aliasing data

$$
\Phi\left(\ell: L^{\vec{q}+\vec{p}}\right)=\Phi\left(\ell: L^{\vec{q}}\right)+\Phi\left(\ell: L^{\vec{p}}\right)
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## Most Complex Constraints: Sharing

$f(x)=g(x, x)$
Assume cost of $\mathbf{g}(\mathbf{x}, \mathrm{y})$ is $10|x| \cdot|y|$

Bound for f is given as $\sum_{i} q_{i}\binom{x}{i}$

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Constraints:

$$
q_{1}=1 \cdot q \quad q_{2}=2 \cdot q \quad q_{k}=0 \cdot q \text { for } k>2
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Need to covert $q|x|^{2}$ to $\sum_{i} q_{i}\binom{x}{i}$
Constraints:

Coefficients for change of basis.
$q_{k}=0 \cdot q$ for $k>2$

## Constraint Solving in Practice

- LP solving of our constraints is linear in practice
- CLP and CPLEX are similar; Ip_solve is slow (non-linear)
- Large programs (with high degree search space) have around 1 million constraints
- Solving 1 million constraints takes about 1 minute with CLP
- Generating the constraints takes about as much time as solving them


## Automatic Amortized Resource Analysis

- Precise: bounds are multivariate resource polynomials
- Efficient: inference via linear programming
- Reliable: formal soundness proof of the bounds
- Verifiable: type derivation is a certificate

Current and future research:

- Non-polynomial bounds
- Garbage collection
- Concurrency
- Better hardware models


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## Web interface at http://raml.co

