Welcome!

On Resource Analysis of Imperative Programs

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ABSTRACT

The execution of a computer program requires resources – time and space. To what extent is it possible to estimate a program's resource requirements by analyzing the program code? Resource analysis has been a fairly popular research area the recent years. I started my research on resource analysis of imperative programs about 13 years ago, and I published my last paper on the subject about a year ago. I will try to share some of the insights I have gained during these years.

The talk will not be very technical, and any computer scientist familiar with elementary complexity theory should be able to follow.

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and
Y:=1; Z:=0;
loop X { loop Y { Z:=Z+2 } Y:=Y+1 }
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Observation I

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Observation II

"circles" can be detected by an algorithm.

I wrote a paper (with NiggI) based on these observations (TCS, 2004).

In this paper we studied a rudimentary imperative programming language manipulating stacks:

push(a,stack) pop(stack) nil(stack)

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- P;Q

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- P;Q
- if top(stack)=symbol then { P }

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- P;Q
- if top(stack)=symbol then { P }
- for each element on stack do { P }

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with the property

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Theorem. A function is computable in polynomial time if, and only if, it can be computed by a program with ν -measure 0.

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Now, ... why characterize complexity classes?

Let me remind you of a few characterizations . . .

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Haven't we seen enough such characterizations by now? Why do we indulge in this business?

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- ... etc.

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- to understand the complexity classes better and shed light upon some of the (notorious hard) open problems of complexity theory
- to understand the computational power of constructions in programming languages
- ... etc.

However, in my and Niggl's case I felt it was rather pointless to characterize *Ptime*, and yet we did! (This was the theorem that the editor and the referee wanted.)

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- the data-flow analysis
- the computational method based on this analysis.

This was a method for estimating the computational complexity of programs.

The method was never explicated in the paper ... just buried down in proofs and theorems.

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, P_1 , P_2 , P_3 , ...

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I noted two things!

On the one hand the set

$$\{P_i \mid P_i \text{ runs in polynomial time}\}$$

is undecidable.

Thus, it is impossible to find a computational method \mathcal{M}' such that

$${P \mid \mathcal{M}'(P) = \text{yes}} = {P \mid P \text{ runs in polynomial time}}$$
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$$\{P \mid \mathcal{M}(P) = \mathsf{yes}\} \ \subset \ \{P \mid \mathcal{M}'(P) = \mathsf{yes}\}$$

$$\subset \ \{P \mid P \text{ runs in polynomial time}\}$$

and

 $\{P \mid \mathcal{M}'(P) = \text{yes}\}\$ contains far more natural programs than $\{P \mid \mathcal{M}(P) = \text{yes}\}.$

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- w-flow
- p-flow

Terminology: *Harmful* things are things that cause a program to compute a value not bounded by a polynomial in the input. (Thus, if a program does not do harmful things, it will run i polynomial time.) *Harmless* things are things that are not harmful.

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This is an example of m-flow:

```
loop U { X:=Y; Y:=Z; Z:=X }.
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This is an example of m-flow:

- no need to put restrictions on m-flow
- "circles" may very well occur.

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This is an example of w-flow:

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loop Z \{ X:=Y+Y; Y:=X \}.
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A "circle" of such flow (inside a loop) will cause a program to compute a value not bounded by a polynomial in the input.

This is an example of w-flow:

loop Z
$$\{ X:=Y+Y; Y:=X \}$$
.

To avoid harmful things, we must put restrictions on w-flow and p-flow.

- w-flow is iteration-independent
- p-flow is iteration-dependent.

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loop
$$X \{ Y := U + V \}$$

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w-flow and p-flow make it possible to distinguish between these to situations.

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The flow graphs were represented matrices.

Here is some of our inference rules:

$$\vdash \mathtt{skip}: \mathbf{1} \qquad \frac{\vdash \mathtt{e}: V}{\vdash \mathtt{X}_j := \mathtt{e}: \mathbf{1} \xleftarrow{j} V}$$

$$\frac{\vdash \mathtt{C}_1 : A \qquad \vdash \mathtt{C}_2 : B}{\vdash \mathtt{C}_1 : \mathtt{C}_2 : A \otimes B} \qquad \frac{\vdash \mathtt{C}_1 : A \qquad \vdash \mathtt{C}_2 : B}{\vdash \mathtt{if b then C}_1 \ \mathtt{else C}_2 : A \oplus B}$$

$$\frac{\vdash \mathtt{C}: M}{\vdash \mathtt{loop} \ \mathtt{X}_{\ell} \ \{\mathtt{C}\}: M^* \oplus \{\stackrel{p}{\ell} \to j \mid \exists \ i \ [M^*_{ij} = p] \ \}} \ (\mathsf{if} \ \forall i [M^*_{ii} = m])$$

Here comes a derivation:

$$\frac{\vdash X_{1}: \binom{m}{0}}{\vdash X_{1}+X_{1}: \binom{p}{0}} \\
\vdash X_{1}+X_{1}: \binom{p}{0}}{\vdash X_{2}:=X_{1}+X_{1}: \binom{m}{0}} \\
\vdash X_{2}:=X_{1}+X_{1}: \binom{m}{0} \quad \stackrel{p}{0} \quad \stackrel{0}{0} \\
0 \quad 0 \quad m$$

$$\vdash 1 \text{cop} X_{3} \{X_{2}:=X_{1}+X_{1}\}: \binom{m}{0} \quad \stackrel{p}{0} \quad \stackrel{0}{0} \\
0 \quad p \quad m$$

Don't try to understand this stuff!

Here is (a part of) another derivation:

A program is *derivable* if the calculus assigns a matrix to the program.

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Theorem.

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Theorem.

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This yields a computational method ${\mathcal M}$ such that

$$\mathcal{M}(P) = \text{yes} \implies P \text{ runs in polynomial time }.$$

(The *mwp*-method.)

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But all this machinery may be good for nothing! How powerful is the *mwp*-method?

The soundness result

$$\mathcal{M}(P) = \text{yes} \implies P \text{ runs in polynomial time}$$

does of course not tell us anything in this respect. (If $\mathcal{M}(P) = no$ for every P, then the method is sound.)

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- (III) Characterize Ptime (and other complexity classes): Prove that for any $f \in Ptime$ there exists a program P such that

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- (III) Characterize Ptime (and other complexity classes): Prove that for any $f \in Ptime$ there exists a program P such that

$$\mathcal{M}(P) = \text{yes and } P \text{ computes } f.$$

(This tells next to nothing, ...it tells that your method can recognize a program that simulates a polynomially clocked Turing machine. It would be very strange if your method couldn't.)

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This is the situation from a more general point of view:

- ullet we want to find an algorithm for solving a problem ${\cal A}$
- but we cannot and we know that cannot because we know that A is undecidable.

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- ullet we want to find an algorithm for solving a problem ${\cal A}$
- but we cannot and we know that cannot because we know that ${\cal A}$ is undecidable.

Recall that a problem is the same as a language. So

 $\mathcal{A} = \{P \mid P \text{ runs in polynomial time}\}$.

An obvious thing to do is

- \bullet to find a subset \mathcal{A}' of \mathcal{A} that in some sense is a good approximation of \mathcal{A}
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If we succeed

- ullet try to find a better approximation \mathcal{A}''
- determine the computational complexity of A'. (P, NP-complete, PSPACE, ...? The better approximation A" will be of a least as high complexity as A')

This seems like a reasonable (and rather obvious) way to proceed. . .

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- a way that may give us some mathematical tools for arguing that our method for estimating the computational complexity of programs works well

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But how do we find good approximations?

(This is the big question.)

We want our approximations to the set

{P | P runs in polynomial time}

to contain as many natural algorithm as possible.

We do not want approximations where we e.g. have imposed restrictions on the nesting depth loops . . . or something like that . . . in general, we do not want restrictions that exclude programs that programmers actually would like to write.

Here is how we (me, Neil Jones and Amir Ben-Amram) found some good approximations.

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We weakened the semantics such that

if

P runs in polynomial time under the weak semantics

then

P runs in polynomial time under the standard semantics.

The set of programs running in polynomial time under the weak semantics turned out to be a decidable set. (But not by the *mwp*-method as I believed.)

The set of programs running in polynomial time under the weak semantics turned out to be a decidable set. (But not by the *mwp*-method as I believed.)

Moreover, this set contains fairly many natural programs. Thus, the set is a good approximation to the set of programs running in polynomial time.

We worked with the language

- if <test> then ... else ...
- loop X { ... }
- X:= expression in *, +, X Y Z... (variables, but no constants)

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- if <test> then ... else ... : non-deterministic choice
- loop X { ... }: non-deterministic loop, the loop variable X gives an upper bound for the number of times the loop will be executed
- the semantics for assignments is the standard one.

lf

P runs in polynomial time under the non-standard semantics

then

P runs in polynomial time under the standard semantics.

lf

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Why?

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Why? Because the only possible execution under the standard semantics corresponds to *one* of the many possible executions under the non-deterministic semantics.

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Why? Because the only possible execution under the standard semantics corresponds to *one* of the many possible executions under the non-deterministic semantics.

Thus, when every execution of the non-deterministic program runs in polynomial time, the only execution of the deterministic program runs in polynomial time.

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Note that Amir could give a counterexample because I could state precisely (mathematically) what I believed the *mwp*-method was able to do.

Amir's example:

```
loop W {
    if ? then
      { Y:= X<sub>1</sub>; Z:= X<sub>2</sub> }
    else
      { Y:= X<sub>2</sub>; Z:= X<sub>1</sub> };
    U:= Y+Z;
    X<sub>1</sub>:= U
    }
```

EXPLAIN ON THE BLACKBOARD.

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Moreover, we proved that this decision problem is in P. (This work is published Springer LNCS proceedings from CiE 2008.)

We worked with standard assignments

$$X := \langle exp \rangle$$

where $\langle exp \rangle$ is a arbitrary expression that may contain variables and the operators + and *.

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But no constants were allowed

(or equivalently, constants are allowed, but the weak semantics interprets a constant as an arbitrary number).

So programs cannot reset variables: X := 0!

Intuitively, it becomes harder to decide if a program runs in polynomial time (under the weak semantics) when programs also can reset variables.

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But now the problem has become *PSPACE*-complete!

A. M. Ben-Amram: On decidable growth-rate properties of imperative programs. (DICE 2010), ed. P. Baillot (volume 23 of EPTCS, ArXiv.org, 2010), pp. 1–14.

So, we are doing better and better.

We can deal with better and better approximations to the set

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Can we do even better? What if we allow the constant 1 in our programming language?

So, we are doing better and better.

We can deal with better and better approximations to the set

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Can we do even better? What if we allow the constant 1 in our programming language?

Then, programs can count: X := X+1!

Can we still decide if a program run in polynomial time?

Open Problem. Let P be a program (in the language give above) that may contain the constants 0 and 1. Is it decidable if P runs in polynomial time under the weak semantics?

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So now we are one the edge of decidability!

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We don't know.

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What do we find in this paper?

Terminology:

A program is *feasible* if every value computed by the program is bounded by polynomials in the inputs.

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A program is *feasible* if every value computed by the program is bounded by polynomials in the inputs.

The *feasibility problem* for the programming language L is the decision problem

input: an L-program P question: Is P feasible?

We consider the feasibility problem for a number of loop languages.

The syntax of a (typical) language we consider:

$$X, Y, Z \in Variable$$
 ::= $X_1 \mid X_2 \mid X_3 \mid ... \mid X_n$
 $C \in Command$::= $X := Y \mid X := Y + Z \mid X := 0 \mid X := Y + 1$
 $\mid C_1; C_2 \mid !loop X \{C\}$

```
We consider two types of loops.
```

```
Definite loops: !loop X \{ \ldots \} (standard loops)
```

```
Indefinite loops: ?loop X \{ \ldots \}
```

We consider three types of assignments.

Standard assignments: $X := \langle exp \rangle$

Max assignments: $X := \max_{n} \langle exp \rangle$

Weak assignments $X := \langle exp \rangle$

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Standard assignments: $X := \langle exp \rangle$

Max assignments: $X := ^{max} \langle exp \rangle$

Weak assignments $X :\leq \langle exp \rangle$

We consider four different forms of $\langle exp \rangle$:

A summary of our results.

expressions:	X+Y	X+Y, O	X+Y, 0, X+1
indefinite loops	PTIME	PSPACE	?
definite loops max ass.	PTIME	PTIME	?
definite loops weak ass.	undecidable	undecidable	undecidable
definite loops standard ass.	undecidable	undecidable	undecidable

Thanks for your attention!

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Thanks to my coauthors: Karl-Heinz Niggl, Neil Jones, Amir Ben-Amram, Jean-Yves Moyen, James Avery.

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... well, maybe I have time for a few more ...