Machine Learning for Proof General: Interfacing Interfaces (Funded by EPSRC First Grant Scheme)

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 - Amazing Examples
 - The bigop library
 - The COQEAL library
 - Formalisation of the Java Virtual Machine

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Further work

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Machine Learning for Proof General







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- Manual handling of various proofs, strategies, libraries, becomes difficult.
- ... team-development is hard, especially that ITPs are sensitive to notation;
- ... comparison of proofs and proof similarities across libraries or even within one big library are hard;

Motivation: machine-learning for automated theorem proving?

Main applications in Automated Theorem Proving:

Where can we use ML?

ML in other areas of (Computer) Science:

Where data is abundant, and needs quick automated classification:

- robotics (from space rovers to small apps in domestic appliences, cars...);
- image processing;
- natural language processing;
- web search;
- computer network analysis;
- Medical diagnostics;
- etc, etc, ...

In all these areas, ML is a common tool-of-the-trade, additional to the primary research specialisation. Will this practice come to Automated theorem proving?

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...where AR does not need help

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.. where we do not trust them

- new theoretical break-throughs (formulation of new theorems);
- giving semantics to data (cf. Deep learning).

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where do we both need ML-tools and trust them?

- finding common proof-patterns in proofs across various scripts, libraries, users, notations;
- providing proof-hints, especially in (industrial) cases where routine similar cases are frequent, and proof development is distributed across several programmers.

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Interfacing-1:



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Solution? – Interfacing



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ITP environment allows the user to "call" ATP for generating solutions.

Automation of interactive proofs: role of interfaces...

Solution? – Interfacing. Example



Automation of interactive proofs: role of interfaces...

Solution? – Interfacing. Example



A note: forward interfacing is easier than backwards interfacing.

Automation of interactive proofs: role of interfaces...

Less familiar alternative:


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Benefits: learning "proof heuristics", speed up in computations. Some success: e.g. work by Stephan Shulz, Joseph Urban.

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Less familiar alternative:



Benefits: helping users to handle big proof developments and libraries. Some attempts: Alan Bundy and Hazel Duncan, current Al4FM project (Edinburgh and Newcastle).

Why machine-learning interactive proofs is harder?

• The richer language reduces the chance of finding regularities and proof patterns by data-mining the syntax alone. Moreover, in ITPs, one and the same goal may have a range of different proofs, whereas different goals can be proven by the same sequence of tactics.

Why machine-learning interactive proofs is harder?

- The richer language reduces the chance of finding regularities and proof patterns by data-mining the syntax alone. Moreover, in ITPs, one and the same goal may have a range of different proofs, whereas different goals can be proven by the same sequence of tactics.
- The notions of a *proof* may be regarded from different perspectives in ITPs: it may be seen as a transition between the subgoals, a combination of applied tactics, or — more traditionally – a proof-tree showing the overall proof strategy.

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Demo...

$$\sum_{1}^{n} i = \frac{n(n+1)}{2}$$

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... new machine-learning extension of Proof General (itself an interface for a variety of ITPs).

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Note: - similarly -

- huge role user interfaces play in Machine-learning community: MATLAB, WEKA, - are famous interfaces to run a range of statistical algorithms.

Our solution: Interfacing Interfaces:



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Outline

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Interaction with ML4PG:

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• User interacts with Proof General as usual,

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- User interacts with Proof General as usual,
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- User interacts with Proof General as usual,
- User gets stuck in a proof,
- User configures ML4PG,
- User calls for a statistical hint,
- ML4PG informs the user of arising proof patterns.

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Problem:

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The most clever part... Feature extraction in ML4PG

Problem:

- statistical ML tools expect, as input, a fixed number of features describing all objects to be classified;
- in higher-order proofs, we cannot fix a finite number of goal shapes or proofs configurations to describe all possible proofs;
- we gather statistics based on a fixed number of implicit proof parameters – proof traces.

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- Neither of the parameters: tactic sequence, goal shape, or argument types is sufficient on its own for drawing conclusions about significant proof patterns;
- For one proof step, the collection of these parameters is insufficient for meaningful proof-pattern recognition;
- Collection of these features over several proof steps a proof trace gives amazing results.

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• Unsupervised machine learning technique:



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• Unsupervised machine learning technique:



- Engines: Matlab, Weka, Octave, R, ...
- Algorithms: K-means, Gaussian Mixture models, simple Expectation Maximisation, . . .

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- Problem:
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This means the ML4PG user does not have to analyse the statistics manually!!!

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Most amazingly... it really works!!!! Demo...

Demo: ML4PG options and various clusters

$$\sum_{1}^{n} i = \frac{n(n+1)}{2}$$
$$\sum_{1}^{n} i^{2} = \frac{n(n+1)(2n+1)}{6},$$
$$\sum_{1}^{n} i^{3} = \frac{n^{4}+2n^{3}+n^{2}}{4},$$
$$\sum_{1}^{n} (2i-1) = n^{2},$$
$$\sum_{1}^{n} (2i-1)^{2} = \frac{4n^{3}-n}{3},$$
$$\sum_{1}^{n} (2i-1)^{3} = 2n^{4}-n^{2}.$$

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Machine Learning for Proof General

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- Applications:
 - Definition of matrix multiplication
 - Binomials
 - Union of sets
 - . . .

Application of ML4PG: Inverse of nilpotent matrices

Definition

Let M be a square matrix, M is nilpotent if it exists an n such that $M^n = 0$

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Let M be a square matrix, M is nilpotent if it exists an n such that $M^n = 0$

Lemma

Let M be a nilpotent matrix, then

$$(1-M) imes \sum_{0 \le i \le n} M^i = 1$$

where *n* is such that $M^n = 0$

Lemma inverse_I_minus_M_big (M : 'M_m) : (exists n, M^n = 0) -> (1 - M) *m (\sum_(0<=i<n) M^i) = 1.

Theorem (Fundamental Lemma of Persistent Homology) $\beta_i^{j,k} : \mathbb{N} \times \mathbb{N} \times \mathbb{N} \to \mathbb{Z}$

$$\beta_n^{k,l} - \beta_n^{k,m} = \sum_{1 \le i \le k} \sum_{1 < j \le m} (\beta_n^{j,p-1} - \beta_n^{j,p}) - (\beta_n^{j-1,p-1} - \beta_n^{j-1,p})$$

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Proof

$$\sum_{1 < i < k} \sum_{l < j \le m} (\beta_n^{j,i-1} - \beta_n^{j,i}) - (\beta_n^{j-1,i-1} - \beta_n^{j-1,i}) =$$

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Suggestions provided by ML4PG

Theorem (Fundamental Lemma of Persistent Homology) $\beta_i^{j,k} : \mathbb{N} \times \mathbb{N} \times \mathbb{N} \to \mathbb{Z}$

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$$\begin{split} &\sum_{1 \leq i \leq k} \sum_{l < j \leq m} (\beta_n^{j,i-1} - \beta_n^{j,i}) - (\beta_n^{j-1,i-1} - \beta_n^{j,-1,i}) &= \\ &\sum_{1 \leq i \leq k} ((\beta_n^{l+1,i-1} - \beta_n^{l+1,i}) - (\beta_n^{l,i-1} - \beta_n^{l,i}) + \\ & (\beta_n^{l+2,i-1} - \beta_n^{l+2,i}) - (\beta_n^{l+1,i-1} - \beta_n^{l+1,i}) + \\ & \dots \\ & (\beta_n^{m-1,i-1} - \beta_n^{m-1,i}) - (\beta_n^{m-2,i-1} - \beta_n^{m-2,i}) + \\ & (\beta_n^{m,i-1} - \beta_n^{m,i}) - (\beta_n^{m-1,i-1} - \beta_n^{m-1,i})) \end{split}$$

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$$\sum_{1 \leq i \leq k} \sum_{\substack{l < j \leq m \\ l \leq i \leq k}} (\beta_n^{j,i-1} - \beta_n^{j,i}) - (\beta_n^{j-1,i-1} - \beta_n^{j-1,i}) = \\ \sum_{1 \leq i \leq k} \underbrace{((\beta_n^{l+1,i-1} - \beta_n^{l+1,i}) - (\beta_n^{l,i-1} - \beta_n^{l,i}) +}_{(\beta_n^{l+2,i-1} - \beta_n^{l+2,i}) - (\beta_n^{l+1,i-1} - \beta_n^{l+1,i}) +}_{\dots} \\ (\beta_n^{m-1,i-1} - \beta_n^{m-1,i}) - (\beta_n^{m-2,i-1} - \beta_n^{m-2,i}) + \\ (\beta_n^{m,i-1} - \beta_n^{m,i}) - (\beta_n^{m-1,i-1} - \beta_n^{m-1,i}))$$

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$$\begin{split} \sum_{1 \leq i \leq k} \sum_{\substack{l < j \leq m}} (\beta_n^{j,i-1} - \beta_n^{j,i}) - (\beta_n^{j-1,i-1} - \beta_n^{j-1,i}) &= \\ \sum_{1 \leq i \leq k} (\underline{(\beta_n^{l+1,i-1} - \beta_n^{l+1,i})} - (\beta_n^{l,i-1} - \beta_n^{l,i}) + \\ \underline{(\beta_n^{l+2,i-1} - \beta_n^{l+2,i})} - (\underline{\beta_n^{l+1,i-1} - \beta_n^{l+1,i})} + \\ \dots \\ \underline{(\beta_n^{m-1,i-1} - \beta_n^{m-1,i})} - (\underline{(\beta_n^{m-2,i-1} - \beta_n^{m-2,i})} + \\ \underline{(\beta_n^{m,i-1} - \beta_n^{m,i})} - (\underline{(\beta_n^{m-1,i-1} - \beta_n^{m-1,i})}) \end{split}$$

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Lemma

If $g:\mathbb{N}\to\mathbb{Z}$, then

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$$\begin{array}{rl} \sum_{0 \leq i \leq k} (g(i+1) - g(i)) &= \\ g(1) - g(0) + g(2) - g(1) + \ldots + g(k+1) - g(k) \end{array}$$

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$$\sum_{\substack{0 \le i < n \\ 0 < i < n}} M^{i} - M^{i+1} =$$

$$M^{0} - M^{1} + M^{1} - M^{2} + \ldots + M^{n-1} - M^{n}$$

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where *n* is such that $M^n = 0$

Proof

$$(1 - M) \times \sum_{\substack{0 \le i < n \\ 0 \le i < n}} M^{i} =$$

$$\sum_{\substack{0 \le i < n \\ 0 \le i < n}} M^{i} - M^{i+1} =$$

$$M^{0} - M^{2} + M^{2} - M^{2} + \dots + M^{n-1} - M^{n}$$

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Suggestions provided by ML4PG

Lemma

Let M be a nilpotent matrix, then

$$(1-M) imes \sum_{0 \le i < n} M^i = 1$$

where *n* is such that $M^n = 0$

Proof

$$\begin{array}{rcl} (1-M) \times \sum\limits_{\substack{0 \leq i < n \\ M^i - M^{i+1} \end{array}} M^i &= \\ M^0 - M^n = M^0 = 1 \end{array}$$

Suggestions provided by ML4PG

Lemma

Let M be a nilpotent matrix, then

$$(1-M) imes \sum_{0 \le i < n} M^i = 1$$

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Proof

$$\begin{array}{rcl} (1-M) \times \sum\limits_{\substack{0 \leq i < n \\ M^i - M^{i+1} \end{array}} M^i &= \\ \sum\limits_{\substack{0 \leq i < n \\ M^0 - M^n = M^0 = 1 \end{array}} M^0 = 1 \end{array}$$

Lemma (Another ML4PG suggestion)

Let M be a nilpotent matrix, then there exists N such that N imes (1 - M) = 1

Katya and Jonathan (Edinburgh)

Machine Learning for Proof General

The COQEAL library

M. Dénès and A. Mörtberg and V. Siles. A refinement-based approach to computational algebra in Coq. In: Proceedings Interactive Theorem Proving 2012 (ITP 2012). Lecture Notes in Computer Science 7406, 83–98. 2012.

M. Dénès and A. Mörtberg and V. Siles. A refinement-based approach to computational algebra in Coq. In: Proceedings Interactive Theorem Proving 2012 (ITP 2012). Lecture Notes in Computer Science 7406, 83–98. 2012.

A methodology, based on the notion of refinement to formalise efficient algorithms of Computer Algebra systems:

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A methodology, based on the notion of refinement to formalise efficient algorithms of Computer Algebra systems:

- Define the algorithm relying on rich dependent types
- 2 Refine it to an efficient version described on high-level data structures
- Implement it on data structures closer to machine representations

Problem

Decipher the key results which can help us to solve our concrete problems

Suppose that we have defined a fast algorithm to compute the inverse of triangular matrices over a field called fast_invmx

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Problems:

• Prove the equivalence with the invmx algorithm of SSReflect

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Problems:

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- Executability of the algorithm

- Clustering with matrix library of SSReflect and CoqEAL library (~ 1000)
- 10 suggestions
- Instead of proving:

```
Lemma fast_invmxE : forall m (M : 'M[R]_m), lower1 M ->
fast_invmx M = invmx M.
```

Suppose that we have defined a fast algorithm to compute the inverse of triangular matrices over a field called fast_invmx

Problems:

- Prove the equivalence with the invmx algorithm of SSReflect
- Executability of the algorithm

- Clustering with matrix library of SSReflect and CoqEAL library (~ 1000)
- 10 suggestions
- Prove:

```
Lemma fast_invmxE : forall m (M : 'M[R]_m), lower1 M ->
    M *m fast_invmx M = 1%:M.
```

```
• Key suggestion:
Lemma invmx_is_uniq : forall m (M1 M2 : 'M[R]_m), M1 *m M2 = 1%:M ->
M2 = invmx M1.
```

Suppose that we have defined a fast algorithm to compute the inverse of triangular matrices over a field called fast_invmx

Problems:

- Prove the equivalence with the invmx algorithm of SSReflect
- Executability of the algorithm

- CoqEAL suggestion: refine the algorithm to work with sequences instead of matrices
- Clustering with CoqEAL library (~ 700)
- 7 suggestions all of them related to the refinement from matrices to sequences

Formalisation of the JVM: example suggested by J Moore

Java Virtual Machine (JVM) is a stack-based abstract machine which can execute Java bytecode

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Java Virtual Machine (JVM) is a stack-based abstract machine which can execute Java bytecode

Goal

- $\bullet\,$ Model a subset of the JVM in ${\rm Coq},$ defining an interpreter for JVM programs
- \bullet Verify the correctness of JVM programs within Coq

Formalisation of the JVM: example suggested by J Moore

Java Virtual Machine (JVM) is a stack-based abstract machine which can execute Java bytecode

Goal

- Model a subset of the JVM in COQ, defining an interpreter for JVM programs
- \bullet Verify the correctness of JVM programs within Coq

This work is inspired by:

H. Liu and J S. Moore. Executable JVM model for analytical reasoning: a study. Journal Science of Computer Programming - Special issue on advances in interpreters, virtual machines and emulators (IVME'03), 57(3):253–274, 2003.

```
Java code:
```

```
static int factorial(int n)
{
    int a = 1;
    while (n != 0){
        a = a * n;
        n = n-1;
        }
    return a;
}
```

Bytecode:

- 0 : *iconst* 1
- 1 : *istore* 1
- 2 : *iload* 0
- 3 : *ifeq* 13
- 4 : *iload* 1
- 5 : iload 0
- 6 : *imul*
- 7 : istore 1
- 8 : *iload* 0
- 9 : *iconst* 1
- 10 : *isub*
- 11 : *istore* 0
- 12 : goto 2
- 13 : iload 1
- 14 : ireturn

Bytecode:

0	:	iconst 1
1	:	istore 1
2	:	iload 0
3	:	ifeq 13
4	:	iload 1
5	:	iload 0
6	:	imul
7	:	istore 1
8	:	iload 0
9	:	iconst 1
10	:	isub
11	:	istore 0
12	:	goto 2
13	:	iload 1
14	:	ireturn

JVM model:

counter: 0

stack:



Bytecode:

0	:	iconst 1
1	:	istore 1
2	:	iload 0
3	:	ifeq 13
4	:	iload 1
5	:	iload 0
6	:	imul
7	:	istore 1
8	:	iload 0
9	:	iconst 1
10	:	isub
11	:	istore 0
12	:	goto 2
13	:	iload 1
14	:	ireturn

JVM model:

counter: 1

stac	:k:			
1				



Bytecode:

0	:	iconst 1
1	:	istore 1
2	:	iload 0
3	:	ifeq 13
4	:	iload 1
5	:	iload 0
6	:	imul
7	:	istore 1
8	:	iload 0
9	:	iconst 1
10	:	isub
11	:	istore 0
12	:	goto 2
13	:	iload 1
14	:	ireturn

JVM model:

counter: 2

sta	acł	C		

loca	al va	aria	ab	les:
-	1			

|--|

Bytecode:

0	:	iconst 1
1	:	istore 1
2	:	iload 0
3	:	ifeq 13
4	:	iload 1
5	:	iload 0
6	:	imul
7	:	istore 1
8	:	iload 0
9	:	iconst 1
10	:	isub
11	:	istore 0
12	:	goto 2
13	:	iload 1
14	:	ireturn

JVM model:

counter: 3

stack:

5 1

Bytecode:

0	:	iconst 1
1	:	istore 1
2	:	iload 0
3	:	ifeq 13
4	:	iload 1
5	:	iload 0
6	:	imul
7	:	istore 1
8	:	iload 0
9	:	iconst 1
10	:	isub
11	:	istore 0
12	:	goto 2
13	:	iload 1
14	:	ireturn

JVM model:

counter: 4

stack:

loca	al va	ari	ab	les:	
E	1				

|--|

Bytecode:

0	:	iconst 1
1	:	istore 1
2	:	iload 0
3	:	ifeq 13
4	:	iload 1
5	:	iload 0
6	:	imul
7	:	istore 1
8	:	iload 0
9	:	iconst 1
10	:	isub
11	:	istore 0
12	:	goto 2
13	:	iload 1
14	:	ireturn

JVM model:

counter: 5

stack:				
1				

5 1

Bytecode:

0	:	iconst 1
1	:	istore 1
2	:	iload 0
3	:	ifeq 13
4	:	iload 1
5	:	iload 0
6	:	imul
7	:	istore 1
8	:	iload 0
9	:	iconst 1
10	:	isub
11	:	istore 0
12	:	goto 2
13	:	iload 1
14	:	ireturn

JVM model:

counter: 6

stack:				
5	1			

5 1

Bytecode:

0	:	iconst 1
1	:	istore 1
2	:	iload 0
3	:	ifeq 13
4	:	iload 1
5	:	iload 0
6	:	imul
7	:	istore 1
8	:	iload 0
9	:	iconst 1
10	:	isub
11	:	istore 0
12	:	goto 2
13	:	iload 1
14	:	ireturn

JVM model:

counter: 7

stack:

5 1

Bytecode:

0	:	iconst 1
1	:	istore 1
2	:	iload 0
3	:	ifeq 13
4	:	iload 1
5	:	iload 0
6	:	imul
7	:	istore 1
8	:	iload 0
9	:	iconst 1
10	:	isub
11	:	istore 0
12	:	goto 2
13	:	iload 1
14	:	ireturn

JVM model:

counter: 8

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5 5		
-----	--	--

Bytecode:

0	:	iconst 1
1	:	istore 1
2	:	iload 0
3	:	ifeq 13
4	:	iload 1
5	:	iload 0
6	:	imul
7	:	istore 1
8	:	iload 0
9	:	iconst 1
10	:	isub
11	:	istore 0
12	:	goto 2
13	:	iload 1
14	:	ireturn

JVM model:

counter: 9

stack:

5

5 5	
-----	--

Bytecode:

0	:	iconst 1
1	:	istore 1
2	:	iload 0
3	:	ifeq 13
4	:	iload 1
5	:	iload 0
6	:	imul
7	:	istore 1
8	:	iload 0
9	:	iconst 1
10	:	isub
11	:	istore 0
12	:	goto 2
13	:	iload 1
14	:	ireturn

JVM model:

counter: 10

stad	:k:		
1	5		

5 5		
-----	--	--

Bytecode:

0	:	iconst 1
1	:	istore 1
2	:	iload 0
3	:	ifeq 13
4	:	iload 1
5	:	iload 0
6	:	imul
7	:	istore 1
8	:	iload 0
9	:	iconst 1
10	:	isub
11	:	istore 0
12	:	goto 2
13	:	iload 1
14	:	ireturn

JVM model:

counter: 11

stad	:k:			
4				

5 5

Bytecode:

0	:	iconst 1
1	:	istore 1
2	:	iload 0
3	:	ifeq 13
4	:	iload 1
5	:	iload 0
6	:	imul
7	:	istore 1
8	:	iload 0
9	:	iconst 1
10	:	isub
11	:	istore 0
12	:	goto 2
13	:	iload 1
14	:	ireturn

JVM model:

counter: 12

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local	varia	nles.
locui	varia	JICJ.

4 5

Bytecode:

0	:	iconst 1			
1	:	istore 1			
2	:	iload 0			
3	:	ifeq 13			
4	:	iload 1			
5	:	iload 0			
6	:	imul			
7	:	istore 1			
8	:	iload 0			
9	:	iconst 1			
10	:	isub			
11	:	istore 0			
12	:	goto 2			
13	:	iload 1			
14	:	ireturn			

JVM model:

counter: 2

sta	acł	C			

local	variah	les.
locui	variab	

4 5

Bytecode:

. . .

JVM model:

. . .

Bytecode:

0	:	iconst 1
1	:	istore 1
2	:	iload 0
3	:	ifeq 13
4	:	iload 1
5	:	iload 0
6	:	imul
7	:	istore 1
8	:	iload 0
9	:	iconst 1
10	:	isub
11	:	istore 0
12	:	goto 2
13	:	iload 1
14	:	ireturn

JVM model:

counter: 13

stad	:k:		
0			

0	120			
---	-----	--	--	--
An example: computing 5!

Bytecode:

0	:	iconst 1			
1	:	istore 1			
2	:	iload 0			
3	:	ifeq 13			
4	:	iload 1			
5	:	iload 0			
6	:	imul			
7	:	istore 1			
8	:	iload 0			
9	:	iconst 1			
10	:	isub			
11	:	istore 0			
12	:	goto 2			
13	:	iload 1			
14	:	ireturn			

JVM model:

counter: 14

stack:						
120						•

local variables:

0	120		
---	-----	--	--

An example: computing 5!

Bytecode:

0	:	iconst 1		
1	:	istore 1		
2	:	iload 0		
3	:	ifeq 13		
4	:	iload 1		
5	:	iload 0		
6	:	imul		
7	:	istore 1		
8	:	iload 0		
9	:	iconst 1		
10	:	isub		
11	:	istore 0		
12	:	goto 2		
13	:	iload 1		
14	:	ireturn		

JVM model:

counter: 15

stack:						
120						•

local variables:

0	120		
---	-----	--	--

Goal (Factorial case)

 $\forall n \in \mathbb{N}$, running the bytecode associated with the factorial program with n as input produces a state which contains n! on top of the stack

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 $\forall n \in \mathbb{N}$, running the bytecode associated with the factorial program with n as input produces a state which contains n! on top of the stack

Methodology:

Definition theta_fact (n : nat) := n'!.

Write the specification of the function

Goal (Factorial case)

 $\forall n \in \mathbb{N}$, running the bytecode associated with the factorial program with n as input produces a state which contains n! on top of the stack

- Write the specification of the function
- Write the algorithm (tail recursive function)

```
Fixpoint helper_fact (n a : nat) :=
match n with
| 0 => a
| S p => helper_fact p (n * a)
end.
```

```
Definition fn_fact (n : nat) :=
    helper_fact n 1.
```

Goal (Factorial case)

 $\forall n \in \mathbb{N}$, running the bytecode associated with the factorial program with n as input produces a state which contains n! on top of the stack

Methodology:

- Write the specification of the function
- Write the algorithm (tail recursive function)
- Prove that the algorithm satisfies the specification

Lemma fn_fact_is_theta n : fn_fact n =
 theta_fact n.

Goal (Factorial case)

 $\forall n \in \mathbb{N}$, running the bytecode associated with the factorial program with *n* as input produces a state which contains *n*! on top of the stack

Definition pi_fact := Methodology: [::(ICONST,1%Z); Write the specification of the function (ISTORE,1%Z); (ILOAD, 0%Z); Write the algorithm (tail recursive) (IFEQ, 10%Z); function) (ILOAD, 1%Z); Prove that the algorithm satisfies the (ILOAD.0%Z): specification (IMUL, 0%Z); Write the JVM program (ISTORE, 1%Z): (ILOAD, 0%Z): (ICONST, 1%Z); (ISUB, 0%Z): (ISTORE, 0%Z); (GOTO, (-10)%Z); (ILOAD, 1%Z); (HALT, 0%Z)].

Goal (Factorial case)

 $\forall n \in \mathbb{N}$, running the bytecode associated with the factorial program with *n* as input produces a state which contains *n*! on top of the stack

- Write the specification of the function
- Write the algorithm (tail recursive function)
- Prove that the algorithm satisfies the specification
- Write the JVM program
- Define the function that schedules the program

```
Fixpoint loop_sched_fact (n : nat) :=
match n with
| 0 => nseq 3 0
| S p => nseq 11 0 ++ loop_sched_fact p
end.
```

```
Definition sched_fact (n : nat) :=
    nseq 2 0 ++ loop_sched_fact n.
```

Goal (Factorial case)

 $\forall n \in \mathbb{N}$, running the bytecode associated with the factorial program with n as input produces a state which contains n! on top of the stack

- Write the specification of the function
- Write the algorithm (tail recursive function)
- Prove that the algorithm satisfies the specification
- Write the JVM program
- Define the function that schedules the program
- Prove that the code implements the algorithm

```
Lemma program_is_fn_fact n :
  run (sched_fact n) (make_state 0 [::n]
      [::] pi_fact) =
  (make_state 14 [::0;fn_fact n ] (push
      (fn_fact n ) [::]) pi_fact).
```

Goal (Factorial case)

 $\forall n \in \mathbb{N}$, running the bytecode associated with the factorial program with *n* as input produces a state which contains *n*! on top of the stack

- Write the specification of the function
- Write the algorithm (tail recursive function)



- Write the JVM program
- Define the function that schedules the program
- Prove that the code implements the algorithm
- Prove total correctness

```
Theorem total_correctness_fact n sf :
  sf = run (sched_fact n) (make_state 0
      [::n] [::] pi_fact) ->
  next_inst sf = (HALT,0%Z) /\
  top (stack sf) = (n'!).
```

- Write the specification of the function
- Write the algorithm (tail recursive function)
- OProve that the algorithm satisfies the specification
- Write the JVM program
- Oefine the function that schedules the program
- O Prove that the code implements the algorithm
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Methodology:

- Write the specification of the function
- Write the algorithm (tail recursive function)
- Prove that the algorithm satisfies the specification
- Write the JVM program
- Optime the function that schedules the program
- O Prove that the code implements the algorithm
- Prove total correctness

Suggestions for fn_fact_is_theta:

fn_expt_is_theta, fn_mult_is_theta, fn_power_is_theta

Methodology:

- Write the specification of the function
- Write the algorithm (tail recursive function)
- OProve that the algorithm satisfies the specification
- Write the JVM program
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- Prove that the code implements the algorithm
- Prove total correctness

Suggestions for program_is_fn_fact: program_is_fn_expt, program_is_fn_mult, program_is_fn_power

Methodology:

- Write the specification of the function
- Write the algorithm (tail recursive function)
- Prove that the algorithm satisfies the specification
- Write the JVM program
- Optime the function that schedules the program
- O Prove that the code implements the algorithm
- Prove total correctness

Suggestions for total_correctness_fact: total_correctness_expt, total_correctness_mult, total_correctness_power

Table of Contents

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 - 4 Amazing Examples
- 5 Further work

Further work

 not only trace successful proofs, but also failed and discarded derivation steps;

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- increase the number of Interactive Theorem Provers and Machine Learning engines;

Further work

- not only trace successful proofs, but also failed and discarded derivation steps;
- increase the number of Interactive Theorem Provers and Machine Learning engines;
- replace local environment with a client-server framework.

"Dundee Fellowship" positions

- University of Dundee is about to announce positions of Dundee Fellows;
- 5-year research fellowship position, becoming a permanent lectureship at the end; starts at 8 point scale;
- Computational was selected as one of a few "named" areas;
- competition will be across several school and departments;
- if you know potential winner please let me know.

Machine Learning for Proof General: Interfacing Interfaces (Funded by EPSRC First Grant Scheme)

Katya Komendantskaya and Jonathan Heras

University of Edinburgh

4 December 2012