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

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Motivation: machine-learning for automated theorem proving?

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 - The CoQEAL library
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- ... 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;

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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- providing proof-hints, especially in (industrial) cases where routine similar cases are frequent, and proof development is distributed across several programmers.

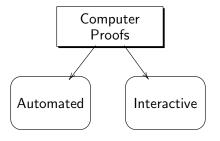
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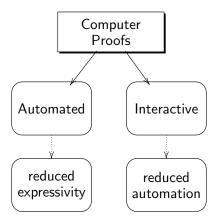
Patty and I are considering using machine-learning to generate hints in undecidable cases of Higher-order unification.

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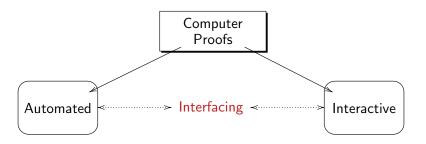
Interfacing-1:



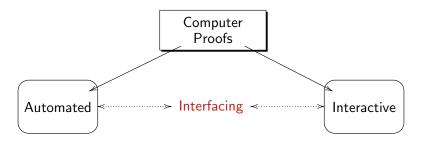
Interfacing-1:



Solution? – Interfacing

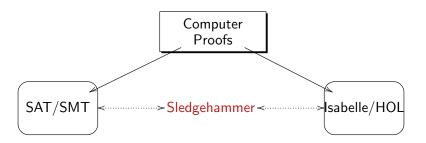


Solution? - Interfacing

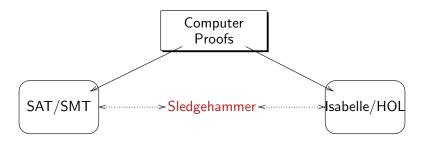


ITP environment allows the user to "call" ATP for generating solutions.

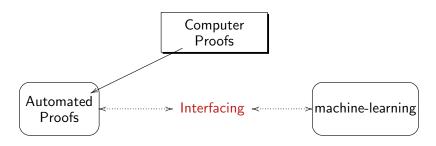
Solution? – Interfacing. Example

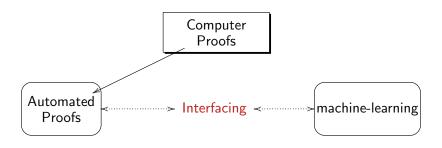


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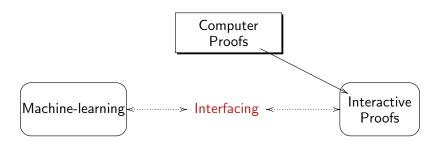
A note: forward interfacing is easier than backwards interfacing.

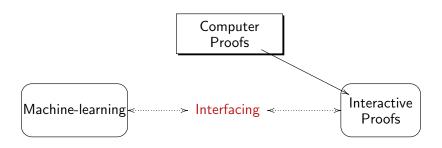




Benefits: learning "proof heuristics", speed up in computations.

Some success: e.g. work by Stephan Shulz, Joseph Urban.





Benefits: helping users to handle big proof developments and libraries. Some attempts: Alan Bundy and Hazel Duncan, current AI4FM 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.

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- 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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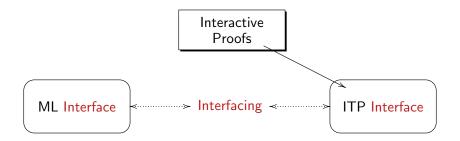
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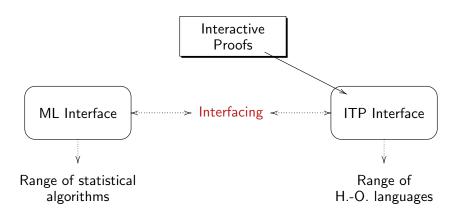
Note: - similarly -

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

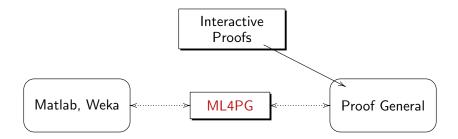
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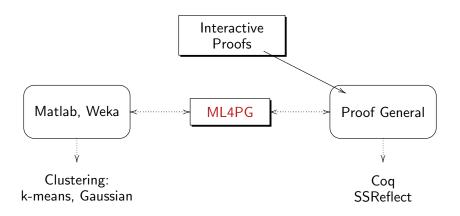
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Our solution: ML4PG:

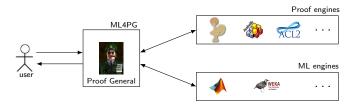


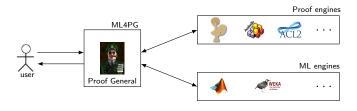
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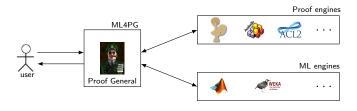


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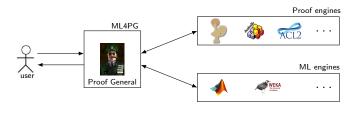




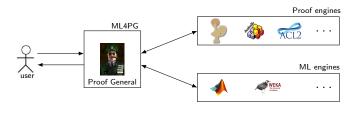


Interaction with ML4PG:

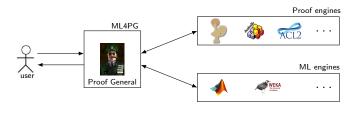
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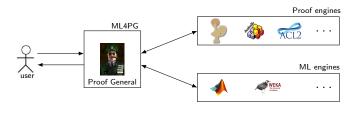
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- User configures ML4PG,
- User calls for a statistical hint,
- ML4PG informs the user of arising proof patterns.

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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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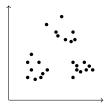
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- Collection of these features over several proof steps a proof trace gives amazing results.

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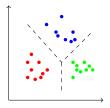
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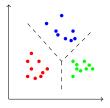
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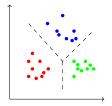
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Unsupervised machine learning technique:



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

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

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Demo...
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Demo: ML4PG options and various clusters

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

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

$$\sum_{1}^{n} i^{3} = \frac{n^{4} + 2n^{3} + n^{2}}{4},$$

$$\sum_{1}^{n} (2i - 1) = n^{2},$$

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

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

Application of ML4PG: Inverse of nilpotent matrices

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Lemma

Let M be a nilpotent matrix, then

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

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 \le i \le n) M^i) = 1.
```

Theorem (Fundamental Lemma of Persistent Homology)

$$\beta_i^{j,k}: \mathbb{N} \times \mathbb{N} \times \mathbb{N} \to \mathbb{Z}$$

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

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$$\beta_i^{j,k}: \mathbb{N} \times \mathbb{N} \times \mathbb{N} \to \mathbb{Z}$$

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

$$\begin{array}{ll} \sum\limits_{1 \leq i \leq k} \sum\limits_{l < j \leq m} (\beta_n^{j,i-1} - \beta_n^{j,i}) - (\beta_n^{j-1,i-1} - \beta_n^{j-1,i}) &= \\ \sum\limits_{1 \leq i \leq k} \underbrace{\left((\beta_n^{l+1,i-1} - \beta_n^{l+1,i}) - (\beta_n^{l,i-1} - \beta_n^{l,i}) + \right.}_{\left. (\beta_n^{l+2,i-1} - \beta_n^{l+2,i}) - (\beta_n^{l+1,i-1} - \beta_n^{l+1,i}) + \right. \\ & \cdot \cdot \cdot \\ \underbrace{\left(\beta_n^{m-1,i-1} - \beta_n^{m-1,i} \right) - (\beta_n^{m-2,i-1} - \beta_n^{m-2,i}) + }_{\left. (\beta_n^{m,i-1} - \beta_n^{m,i}) - (\beta_n^{m-1,i-1} - \beta_n^{m-1,i-1}) \right)} \end{array}$$

Theorem (Fundamental Lemma of Persistent Homology)

$$\beta_i^{j,k}: \mathbb{N} \times \mathbb{N} \times \mathbb{N} \to \mathbb{Z}$$

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

$$\begin{array}{ll} \sum\limits_{1 \leq i \leq k} \sum\limits_{l < j \leq m} (\beta_n^{j,i-1} - \beta_n^{j,i}) - (\beta_n^{j-1,i-1} - \beta_n^{j-1,i}) &= \\ \sum\limits_{1 < i < k} (\beta_n^{m,i-1} - \beta_n^{m,i}) - (\beta_n^{l,i-1} - \beta_n^{l,i}) = \dots \end{array}$$

Lemma

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

$$\sum_{0 < i < k} (g(i+1) - g(i)) = g(k+1) - g(0)$$

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$$\sum_{0 \le i \le k} (g(i+1) - g(i)) = g(1) - g(0) + g(2) - g(1) + \dots + g(k+1) - g(k)$$

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Lemma

Let M be a nilpotent matrix, then

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

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

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

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

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

Suggestions provided by ML4PG

Lemma

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Proof

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

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

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

Lemma (Another ML4PG suggestion)

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



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.



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



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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:

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Suggestions:

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

Suggestions:

- 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

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- Executability of the algorithm

Suggestions:

- Clustering with matrix library of SSReflect and CogEAL 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

Suggestions:

- 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

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

Formalisation of the JVM: example suggested by J Moore

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Goal

- Model a subset of the JVM in CoQ, defining an interpreter for JVM programs
- ullet Verify the correctness of JVM programs within ${
 m Coq}$

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:

```
iconst 1
         istore 1
         iload 0
3
        ifeq 13
        iload 1
5
         iload 0
         imul
         istore 1
8
         iload 0
9
         iconst 1
10
         isub
11
         istore 0
12
        goto 2
13
         iload 1
```

ireturn

14

Bytecode:

iconst 1 istore 1 iload 0 3 ifeq 13 iload 1 5 iload 0 imul istore 1 8 iload 0 iconst 1 10 isub 11 istore 0 12 goto 2 13 iload 1 14 ireturn

JVM model:

counter:

0

stack:





Bytecode:

iconst 1 istore 1 iload 0 ifeq 13 iload 1 5 iload 0 imul istore 1 8 iload 0 iconst 1 10 isub 11 istore 0 12 goto 2 13 iload 1 14 ireturn

JVM model:

counter:

1

stack:

-				
		٠.		



Bytecode:

iconst 1 istore 1 iload 0 3 ifeq 13 iload 1 5 iload 0 imul istore 1 8 iload 0 iconst 1 10 isub 11 istore 0 12 goto 2 13 iload 1 14 ireturn

JVM model:

counter:

2

stack:



local variables:

5 1 ...

Bytecode:

iconst 1 istore 1 iload 0 3 ifeq 13 iload 1 5 iload 0 imul istore 1 8 iload 0 iconst 1 10 isub 11 istore 0 12 goto 2 13 iload 1 14 ireturn

JVM model:

counter:

3

stack:

ſ	5						
	_		٠.	•	•	•	



Bytecode:

iconst 1 istore 1 iload 0 3 ifeq 13 iload 1 5 iload 0 imul istore 1 8 iload 0 iconst 1 10 isub 11 istore 0 12 goto 2 13 iload 1 14 ireturn

JVM model:

counter:

4

stack:





Bytecode:

iconst 1 istore 1 iload 0 3 ifeq 13 iload 1 5 iload 0 imul istore 1 8 iload 0 iconst 1 10 isub 11 istore 0 12 goto 2 13 iload 1

JVM model:

counter:

5

stack:



local variables:

```
5 1 | ...
```

ireturn

14

Bytecode:

iconst 1 istore 1 iload 0 ifeq 13 iload 1 5 iload 0 imul istore 1 8 iload 0 iconst 1 10 isub 11 istore 0 12 goto 2 13 iload 1 14 ireturn

JVM model:

counter:

6

stack:

5	1			
_	_		 -	-

local variables:

5 1 ...

Bytecode:

iconst 1 istore 1 iload 0 ifeq 13 iload 1 5 iload 0 imul istore 1 8 iload 0 iconst 1 10 isub 11 istore 0 12 goto 2 13 iload 1 14 ireturn

JVM model:

counter:

7

stack:

5			

local variables:

5 1 ...

Bytecode:

iconst 1 istore 1 iload 0 3 ifeq 13 iload 1 5 iload 0 imul istore 1 8 iload 0 iconst 1 10 isub 11 istore 0 12 goto 2 13 iload 1 14 ireturn

JVM model:

counter:

8

stack:



```
5 5 ...
```

Bytecode:

iconst 1 istore 1 iload 0 3 ifeq 13 iload 1 5 iload 0 imul istore 1 8 iload 0 iconst 1 10 isub 11 istore 0 12 goto 2 13 iload 1 14 ireturn

JVM model:

counter:

9

stack:



local variables:

5 5 ...

Bytecode:

iconst 1 istore 1 iload 0 3 ifeq 13 iload 1 5 iload 0 imul istore 1 8 iload 0 iconst 1 10 isub 11 istore 0 12 goto 2 13 iload 1 14 ireturn

JVM model:

counter:

10

stack:

1	5			



Bytecode:

iconst 1 istore 1 iload 0 ifeq 13 iload 1 5 iload 0 imul istore 1 8 iload 0 iconst 1 10 isub 11 istore 0 12 goto 2 13 iload 1 14 ireturn

JVM model:

counter:

stack:

11

4			

5	5			

Bytecode:

iconst 1 istore 1 iload 0 3 ifeq 13 iload 1 5 iload 0 imul istore 1 8 iload 0 iconst 1 10 isub 11 istore 0 12 goto 2 13 iload 1 14 ireturn

JVM model:

counter:

12

stack:





Bytecode:

iconst 1 istore 1 iload 0 3 ifeq 13 iload 1 5 iload 0 imul istore 1 8 iload 0 iconst 1 10 isub 11 istore 0 12 goto 2 13 iload 1 14 ireturn

JVM model:

counter:

stack:





Bytecode: JVM model:

An example: computing 5!

Bytecode:

iconst 1 istore 1 iload 0 3 ifeq 13 iload 1 5 iload 0 imul istore 1 8 iload 0 iconst 1 10 isub 11 istore 0 12 goto 2 13 iload 1 14 ireturn

JVM model:

counter:

13

stack:



local variables:

```
0 | 120 | | ...
```

An example: computing 5!

Bytecode:

iconst 1 istore 1 iload 0 3 ifeq 13 iload 1 5 iload 0 imul istore 1 8 iload 0 iconst 1 10 isub 11 istore 0 12 goto 2 13 iload 1 14 ireturn

JVM model:

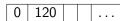
counter:

14

stack:

120		

local variables:



An example: computing 5!

Bytecode:

iconst 1 istore 1 iload 0 3 ifeq 13 iload 1 5 iload 0 imul istore 1 8 iload 0 iconst 1 10 isub 11 istore 0 12 goto 2 13 iload 1

JVM model:

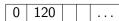
counter:

stack:

15

120		

local variables:



ireturn

14

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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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)
- Or 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

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

```
Definition pi_fact :=
  [::(ICONST,1%Z);
     (ISTORE, 1%Z);
     (ILOAD, 0\%Z);
     (IFEQ, 10%Z);
     (ILOAD, 1%Z);
     (ILOAD.0%Z):
     (IMUL, 0%Z);
     (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)
- Opening Prove that the algorithm satisfies the specification
- Write the JVM program
- Define the function that schedules the program
- O 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)
- Opening Prove that the algorithm satisfies the specification
- Write the JVM program
- Oefine 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)
- 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
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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
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- 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)
- Prove that the algorithm satisfies the specification
- Write the JVM program
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Suggestions for program_is_fn_fact: program_is_fn_expt, program_is_fn_mult, program_is_fn_power

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```
Suggestions for total_correctness_fact:
total_correctness_expt, total_correctness_mult,
total_correctness_power
```

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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.

Job add

- University of Dundee is about to announce positions of Dundee Fellows;
- 5-year fellow position, becoming a permanent lectureship at the end; starts at 8 point scale;
- ITPs were 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 Dundee

30 November 2012