Statistical Machine Learning in Interactive Theorem Proving

Katya Komendantskaya and Jonathan Heras (Funded by EPSRC First Grant Scheme)

University of Dundee

18 July 2014





Existing tools and challenges



2 ML4PG: "Machine Learning for Proof General"



2 ML4PG: "Machine Learning for Proof General"





- 2 ML4PG: "Machine Learning for Proof General"
- 3 Conclusions and Further work
- 4 Using ML4PG: Demo

- ... size and sophistication of libraries stand on the way of efficient knowledge reuse;
 - ... applied in formal mathematical proofs: Four Colour Theorem (60,000 lines), Kepler conjecture (325,000 lines), Feit-Thompson Theorem (170,000 lines), etc.
 - ... applied in industrial proofs: seL4 microkernel (200,000 lines), verified C compiler (50,000 lines), ARM microprocessor (20,000 lines), etc.

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- ... team-development is hard, especially as ITPs are sensitive to notation;

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- ... manual handling of various proofs, strategies, libraries, becomes difficult;
- ... team-development is hard, especially as ITPs are sensitive to notation;
- ... comparison of proof similarities is hard.

Existing tools for managing Coq libraries: Search

Several searching tools in Coq:

- Search , SearchAbout, SearchPattern and SearchRewrite.
- SSReflect implements its own version Search with functionality the 4 Coq's search commands.

```
Example
Search "distr"in bigop
Search _ (_ * (\big[_/_]_(_ <- _| _)_))
```

• The Whelp platform is a web search engine in Coq code, whith 3 functions:

Match (similar Search),

Hint (finds all the theorems which can be applied to derive the current goal) and

Elim (retrieves all the eliminators of a given type).

Main properties of the search engines:

- goal oriented
- hence the user should already know what he is searching for: pattern/library/lemma name, etc
- deterministic: if the exact requested pattern exists, they will find it.

Existing tools-2: Dependency graphs

- You do not have to know what you are searching for
- They show "all there is".



Existing tools-2: Dependency graphs

• or perhaps all there is relative to your lemma/term



Dependency graphs DOs and DON'Ts

- nicely visualised
- not goal directed but can be used for a goal
- deterministic: if there is a dependency, it will be shown
- but it would not tell you if there are similar lemmas/terms
- it would not tell you which of those dependencies are more important than others for the proof
- there may be excessive information that actually hides the essence of the proof

The missing tool...

Something that could help us to:

- capture and search the meaning of the libraries;
- the higher-level proof strategies beyond tactics and notations
- identify redundancies and repetitions....

Motivating example:

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

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

Apply case on n.

- Prove the base case (a simple task).
- 2 Prove the case 0 < n:
 - expand the summation,
 - cancel the terms pairwise,
 - the only terms remaining after the cancellation are the first and the last one.

Same strategy:

Lemma

Let M be a nilpotent matrix, then

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

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

Lemma

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

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

Lemma

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

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Statistical Machine Learning in ITP

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Outline



2 ML4PG: "Machine Learning for Proof General"





Proof pattern recognition in ITPs

Goal: make machine-learning a part of interactive proof development Apply machine-learning methods to:

- find common proof-patterns in proofs across various scripts, libraries, users and notations;
- provide proof-hints in real-time and relative to a proof stage;
- assist the user, not the prover.

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ML4PG:

 Proof General extension which applies machine learning methods to Coq/SSReflect proofs. [Now available in standard Proof General distribution]

E. Komendantskaya, J. Heras and G. Grov. Machine learning in Proof General: interfacing interfaces. EPTCS Post-proceedings of User Interfaces for Theorem Provers. 2013.

Machine Learning 4 Proof General: interfacing interfaces



Machine Learning 4 Proof General: interfacing interfaces



- **F.1.** works on the background of Proof General extracting some low-level features from proofs in Coq/SSReflect.
- **F.2.** automatically sends the gathered statistics to a chosen machine-learning interface and triggers execution of a clustering algorithm of user's choice;
- **F.3.** does some post-processing of the results and displays families of related proofs to the user.

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• Unsupervised machine learning technique:



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We have integrated Proof General with a variety of clustering algorithms:

• Unsupervised machine learning technique:



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

Feature extraction and output strategies



Feature extraction



Feature Extraction for Terms

specifically developed for Coq and ML4PG

Terms are understood broadly: ...Definitions, type declarations, (co)fixpoint function definitions, lemma and theorem statements...

Example forall (n : nat) (H : even n), odd (n + 1).

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its topology



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What populates its nodes:



- its topology
- What populates its nodes:
 - terms and their types



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- What populates its nodes:
 - terms and their types
 - definitions of those terms and types, their meaning and structure...
 - their role in this proof library...
| | level index 0 | level index 1 | level index 2 |
|-----|---|------------------------------------|---|
| td0 | $([\texttt{forall}]_{Gallina},-1,-1)$ | (0,0,0) | (0,0,0) |
| td1 | $([n]_{term}, [nat]_{type}, 0)$ | $([H]_{term}, [even n]_{type}, 0)$ | $([odd]_{term}, [nat->Prop]_{type}, 0)$ |
| td2 | $([+]_{term}, [nat->nat->nat]_{type}, 2)$ | (0,0,0) | (0,0,0) |
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- The function [.] gives the meaning:
- it is defined recurrently and adaptively, using clustering, for every given library and proof-stage;
- ...starts with Gallina pre-defined symbols, and uses them to find similarity of the first few Coq definitions; and then proceeds recursively.
- The more two terms or types are "semantically similar", the closer values they get. Thus, this matrix should have similar content to e.g. the matrix of forall (n : nat) (H : odd n), even (n + 1).

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Motivation for this feature extraction:

For each term, we get a matrix of size up to 300 features, which capture:

- term-tree structure of that term via the term-depth, level-size, and additional "third" feature relating the above;
- its types as related to terms; (pattern-recognition tools analyse the relative values of all features, as 1 Coq object is a point in 300-dimensional space)
- its dependency to other definitions and Coq terms types via recurrent clustering

A simple example

General library clustering:

SSReflect Base library, 12 standard files, 457 terms, 91 clusters (the number and size of clusters can be changed using PG options); 5-10 seconds.

Example

```
Fixpoint eqn (m n : nat) :=
match m, n with
| 0, 0 => true
| m'.+1, n'.+1 => eqn m' n'
| _, _ => false end.
Fixpoint eqseq (s1 s2 : seq T) :=
match s1, s2 with
| [::], [::] => true
| x1 :: s1', x2 :: s2' => (x1 == x2) && eqseq s1' s2'
| _, _ => false end.
```

Note: common structure across types and type constructors

A simple example

General library clustering:

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Example

```
Fixpoint drop n s := match s, n with
| _ :: s', n'.+1 => drop n' s'
| _, _ => s end.
Fixpoint take n s := match s, n with
| x :: s', n'.+1 => x :: take n' s'
| _, _ => [::] end.
```

Intuitive...

A simple example

General library clustering:

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Example

```
Definition flatten := foldr cat (Nil T).
```

```
Definition sumn := foldr addn 0.
```

Analyses deep into structures of subterms by recurrent clustering: cat and addn are defined on lists and natural numbers, but are in the same cluster recurrently. These 2 grouped together out of 15 other definitions using foldr.

• Goal-oriented clustering: do the same but show only what is related to certain Coq object: e.g. related to flatten. (See demo)

ML4PG



Proof-clustering

Similarly to term-clustering, the feature extraction:

- relies on recurrently computed features;
- considers a fragment of a proof-tree a proof-patch to find relative dependencies between goals, tactics and tactic arguments;
- considers relation of the tactic arguments to the (inductive) hypotheses or library lemmas.

As before,

- a 5-step proof patch is given by 85 features;
- each proof patch is a point in 85-dimensional space;
- the proof pattern is determined by looking at their correlation in several proofs.

A proof-feature algorithm by example

HoTT Path library

```
Lemma dpath_path_l A : Type x1 x2 y : A
(p : x1 = x2) (q : x1 = y) (r : x2 = y) :
q = p @ r <~> transport (fun x => x = y) p q = r.
Proof.
destruct p; simpl.
exact (equiv_concat_r (concat_1p r) q).
Qed.
Lemma transport_paths_lr A : Type x1 x2 : A (p : x1 = x2) (q : x1 = x1)
: transport (fun x => x = x) p q = p^ @ q @ p.
Proof.
destruct p; simpl.
exact ((concat_1p q)^ @ (concat_p1 (1 @ q))^ ).
Qed.
```

A proof-feature algorithm by example

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Proof.

destruct p; simpl.

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Qed.
```

	tactics	n	arg type	arg	symbols	goal
g1	([destruct] _{tac} , [simpl] _{tac} , 0, 0)	2	([paths x1 x2] _{type} 0,0,0)	([p] _{term} , 0, 0, 0)	([<∼>] _{term} , [=] _{term} , [=] _{term})	1
g2	([exact] _{tac} , 0,0,0)	1	$([Prop]_{type}, 0, 0, 0)$	<pre>([(equiv_concat_r(concat_1p r)q)]terr 0,0,0)</pre>	$n, ([<\sim>]_{term}, [=]_{term}, [=]_{term})$	0

Proof-patch analysis

Knowing how to prove Lemma dpath_path_1, what else can I prove?



ML4PG: visualisation



ML4PG: visualisation



Visualisation: HoTT library Term Similarity Graph

isequiv_moveL_1M		isequiv_movel_1V	isequiv_movel_V1
isequiv_moveR_Mp	isequiv_moveR_Vp	isequiv_moveR_pV	isequiv_moveL_pM
vert_vert_vert_vert_vert_vert_vert	isequiv_cancelL	isequiv_cancelR	
isequiv_moveR_M1	isequiv_moveR_1M		
isequiv_moveR_1V	isequiv_moveR_V1		
dpath_path_FFIr	dpath_path_IFFr		
dpath_path_ir			
dpath_path_l	dpath_path_r	dpath_path_FI	dpath_path_Fr
dpath_path_FIFr			
transport_paths_FIFr_D			
transport_paths_IFFr			
transport_paths_Fr			
equiv_ap_l			
transport_paths_l			
equiv_concet_l			
transport_paths_FFir			
equiv_inj			
isequiv_moveR_transport_V		isequiv_movel_transport_p	
isequiv_moveR_transport_p			

ML4PG: visualisation



Visualisation: HoTT library Proof Similarity Graph



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3 Conclusions and Further work



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- Request a proof-hint during an on-going proof-development;
- Import a proof methodology from a different library;
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- Share work-load in a team development.
- J. Heras and K. Komendantskaya. ML4PG in Computer Algebra Verification. MKM/Calculemus/DML 2013: 354-358.
- J. Heras and K. Komendantskaya. Recycling Proof-Patterns in Coq: Case Studies. MCS, 2014.

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- tolerant to mixing and matching different proof libraries and different notation used in proofs across different users.
- ML4PG is now a part of standard Proof General distribution.

	Search	Dependency graphs	ML4PG
Method	Search	Parsing	Statistical Pattern- recognition
Goal-oriented?			
Deterministic?			
Visual representation			
Covers proofs or terms?			
Takes into consideration depen- dencies?			
Finds structural similarities be- yond concrete syntax?			
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Good for proof automation?			

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Percentage of atomtaically re-proven theorems:

Library	Granularity 1	Granularity 3	Granularity 5
ssrnat (SSReflect)	48%	36%	28%
seq (SSReflect)	21%	20%	15%
ssrbool (SSReflect)	70%	77%	62%
fintype (SSReflect)	7%	7%	9%
JVM	56%	58%	65%
summations	0%	10%	12%
Paths (HoTT)	92%	91%	94%
Nash Equilibrium	40%	37%	36%

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Can we use ML4PG to automatically prove theorems?

Given the statement of a theorem T and the associated library L, we can use ML4PG to try to find a proof for T as follows:

- Use ML4PG to obtain the cluster C from the library L that contains the theorem T.
- Obtain the sequence of tactics { Tⁱ₁,..., Tⁱ_{ni}}_i used to prove each lemma in C.
- Solution For each *i*, try to prove *T* using $T_1^i, \ldots, T_{n_i}^i$.
- If no sequence of tactics prove T, then for each tactic use ML4PG to infer the argument for each tactic Tⁱ_i:
 - If the argument of T_j^i is an internal hypothesis from the context of a proof, try all the internal hypothesis from the context of the current proof.
 - If the argument of T_j^i is an external lemma *L*, use ML4PG to compute all the lemmas in the same cluster as *L* and try all those lemmas.
 - *** This can be naturally extended to tactics with several arguments, just trying all the possible combinations.

Katya and Jónathan (Dundee) Statistic

Statistical Machine Learning in ITP