

# MaLeCoP

## Machine Learning Connection Prover

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Motivation: ATP in complex mathematical theories

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MaLeCoP - Machine Learning Connection Prover

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# Reasoning in complex mathematical theories

- ▶ Large formal theories recently built with proof assistants
- ▶ Many advanced proofs containing many ideas
- ▶ We should be able to re-use them!
- ▶ Mizar Mathematical Library (set theory) - 100k facts/proofs
- ▶ Isabelle/HOL - translated to first-order logic - 20k facts
- ▶ We want strong automated reasoning support for such systems
- ▶ "Sledgehammer" already popular among Isabelle/HOL users

# The MPTP Challenge benchmark

- ▶ 2006/7: Bring large-theory problems to ATP developers
- ▶ Predecessor and initial design of the CASC LTB category (2008)
- ▶ 252 Mizar problems leading to Bolzano-Weierstrass theorem
- ▶ All previous theorems/definitions available for each problem
- ▶ More than thousand of formulas in some problems

# Successful large-theory techniques

- ▶ Symbol-based premise selection heuristics (SInE, Sledgehammer, MaLAREa)
- ▶ Goal-directed calculi (LeanCoP, some E prover's strategies)
- ▶ Model-based (semantic) premise selection (Vyskocil, Pudlak, MaLAREa, SRASS)
- ▶ Learning premise relevance from proofs (MaLAREa)

## Our goal here:

- ▶ Improve “standard” ATPs by applying the successful large-theory techniques
- ▶ Plan: guide ATPs’ internal inference analogously to guiding premise selection
- ▶ This should allow ATPs to solve harder problems

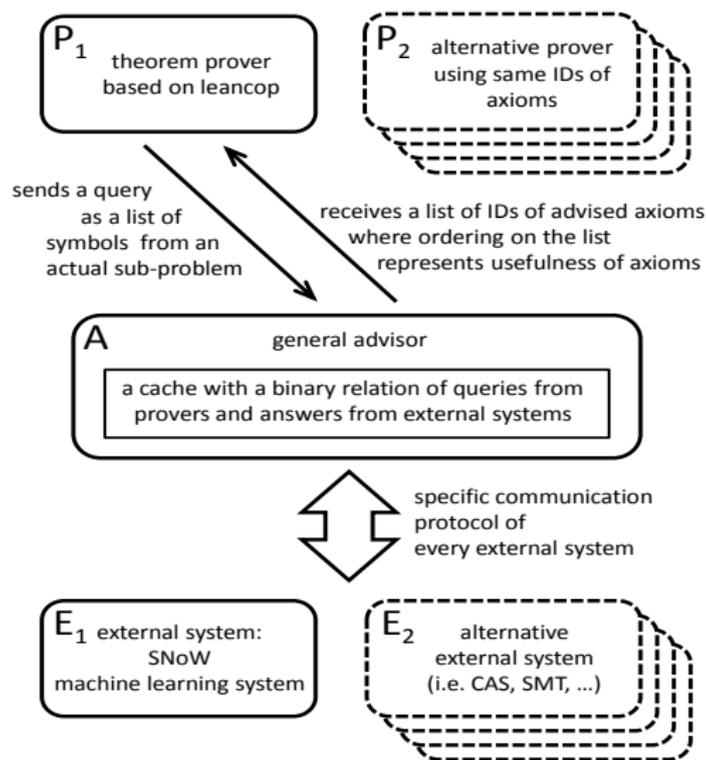
# Machine Learner for Automated Reasoning (MaLAREa)

- ▶ Solve some unsolved problems
- ▶ Use solutions to learn relevance of premises for conjectures
- ▶ Use only a fragment of the most relevant premises for the unsolved problems
- ▶ Loop (combining learning with ATPs and model finders)

# LeanCoP: Lean Connection Prover

- ▶ Connected tableau calculus - goal oriented
- ▶ Very good performance on the MPTP Challenge (better than SPASS)
- ▶ Tableau seems more suitable than resolution for guiding clause selection
- ▶ Compact Prolog implementation - easy to modify
- ▶ This already allowed quite advanced combinations of strategies (and so we hope for more)

# General Advising Design



# LeanCoP modifications

- ▶ Consistent classification across many problems needed for consistent learning/advice
- ▶ Options like definition introduction need to be fixed
- ▶ Providing training data for external advising systems
- ▶ Mechanisms for taking advice from external system(s)
- ▶ Profiling mechanisms
- ▶ External advice is quite slow: number of strategies defined trading advice for speed

## External advice

- ▶ Now used for clause selection when extending the tableau
- ▶ Needs to be reasonably fast and general
- ▶ The SNoW system (naive Bayes, C++) used
- ▶ Library of functions implementing fast caching, communication, data translation

# Strategies for Guidance

- ▶ advising every clause selection step is very slow
- ▶ dozen parametrized strategies and meta-strategies
- ▶ trade fast blind raw inference for slower guided inference
- ▶ trade caching the guidance in Prolog for memory
- ▶ trade (theoretical) completeness for speed by focusing only on relevant clauses
- ▶ Example: ask for advice only when there are many matching clauses
- ▶ Example: ask for advice only for a small number of initial steps
- ▶ Example: use one global relevance order instead of local ones for each path

# Experiments: Proof Search Shortening

- ▶ First solve as many of the 252 MPTP Challenge problems as possible with LeanCoP
- ▶ 73 problems solved, providing 703 training examples for the advisor
- ▶ Then SNoW trained and run as a daemon, advising following MaLeCoP runs on the problems
- ▶ The number of extension steps drops 20 times on average
- ▶ All 73 problems solved again

# Experiments: Solving New Problems

- ▶ Seven strategies tested on the unsolved problems
- ▶ The most successful solves eight more problems
- ▶ All seven solve fifteen more problems
- ▶ Not directly comparable to MaLAREa (no looping yet, etc.)
- ▶ Finer guidance seems to generally help more than just course initial relevance-ordering

# Experiments: Solving New Problems

1. `leancop_ala_malarea`
2. `limited_smart_with_first_advice(3)`
3. `scalable_with_first_advice(40,limited_smart_and_complete_with_fa(3))`
4. `scalable_with_first_advice(3,20,original_leancop)`
5. `limited_smart_with_first_advice(4)`
6. `scalable_with_first_advice(3,20,limited_smart_with_first_advice(5))`
7. `limited_smart_and_complete_with_first_advice(3)`

# Solving New Problems

problem	1	2	3	4	5	6	7
t26_finset_1						4033	
t72_funct_1	1310						
t143_relat_1		28458	59302				61660
t166_relat_1		17586			4067	5263	
t65_relat_1					79756	36217	
t43_subset_1		82610					
t16_wellord1					37148		
t18_wellord1			3517	2689			2524
t33_xboole_1	3659	16456				16902	17925
t40_xboole_1		16488			15702		28404
t30_yellow_0	24277						
l2_zfmisc_1							85086
l3_zfmisc_1							79786
l4_zfmisc_1		17074			9584	14299	30273
t9_zfmisc_1			80684				77532

## Future Work and Conclusion

- ▶ ATP system that can use dynamic external low-level guidance and provides low-level training information to external AI systems
- ▶ ATP/learning architecture that is more deeply integrated than other systems
- ▶ This poses new interesting problems, but it already seems to practically work

### Future work:

- ▶ Better strategies, better profiling, faster advice
- ▶ Investigate the trade-off between completeness and relevance
- ▶ Integrate more techniques used in MaLAREa: semantic selection, looping
- ▶ Learn even on unsuccessful proofs how to avoid bad choices
- ▶ Integrate other kinds of systems (CASes like LeanCoP-Omega?)
- ▶ Try detecting terminating classes of inputs/outputs
- ▶ ...