COMBINING LEARNING AND DEDUCTION OVER FORMAL MATH CORPORA

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Outline

Motivation, Learning vs. Reasoning

Computer Understandable (Formal) Math

Learning of Theorem Proving

Examples and Demos

High-level Reasoning Guidance: Premise Selection

Low Level Guidance of Theorem Provers

Mid-level Reasoning Guidance

More on Neural Guidance, Synthesis and Conjecturing

Autoformalization

How Do We Automate Math and Science?

- What is mathematical and scientific thinking?
- Pattern-matching, analogy, induction from examples
- Deductive reasoning
- Complicated feedback loops between induction and deduction
- Using a lot of previous knowledge - both for induction and deduction

- We need to develop such methods on computers
- Are there any large corpora suitable for nontrivial deduction?
- Yes! Large libraries of formal proofs and theories
- So let's develop strong AI on them!

What is Formal Mathematics?

- Developed thanks to the Leibniz/Russell/Frege/Hilbert/... program
- Mathematics put on formal logic foundations (*symbolic computation*)
- ... which btw. led also to the rise of computers (Turing/Church, 1930s)
- Formal math (1950/60s): combine formal foundations and the newly available computers
- De Bruijn, Milner, Trybulec, Boyer and Moore, Gordon, Huet, Paulson, ...
- Automath, LCF, Mizar, NQTHM and ACL2, HOL, Coq, Isabelle, ...
- Conceptually very simple:
- Write all your axioms and theorems so that computer understands them
- Write all your inference rules so that computer understands them
- Use the computer to check that your proofs follow the rules
- But in practice, it turns out not to be so simple
- Many approaches, still not mainstream, but big breakthroughs recently

History and Motivation for AI/TP

- Intuition vs Formal Reasoning – Poincaré vs Hilbert, Science & Method
- Turing's 1950 paper: Learning Machines, learn Chess?, undecidability??
- Lenat, Langley, etc: manually-written heuristics, learn Kepler laws,...
- Denzinger, Schulz, Goller, Fuchs – late 90's, ATP-focused:
- *Learning from Previous Proof Experience*
- My MSc (1998): Try ILP to learn rules and heuristics from IMPS/Mizar
- Since: Use large formal math (Big Proof) corpora: Mizar, Isabelle, HOL
- ... to combine/develop symbolic/statistical deductive/inductive ML/TP/AI
- ... hammer-style methods, feedback loops, internal guidance, ...
- More details – AGI'18 keynote: `https://bit.ly/3qifhg4`
- AI vs DL: Ben Goertzel's Prague talk: `https://youtu.be/Zt2HSTuGBn8`
- Big AI visions: automate/verify math, science, law, (Leibniz, McCarthy, ..)
- Practical impact: boost today's large ITP verification projects

Using Learning to Guide Theorem Proving

- **high-level**: pre-select lemmas from a large library, give them to ATPs
- **high-level**: pre-select a good ATP strategy/portfolio for a problem
- **high-level**: pre-select good *hints* for a problem, use them to guide ATPs
- **low-level**: guide every inference step of ATPs (tableau, superposition)
- **low-level**: guide every kernel step of LCF-style ITPs
- **mid-level**: guide application of tactics in ITPs
- **mid-level**: invent suitable ATP strategies for classes of problems
- **mid-level**: invent suitable conjectures for a problem
- **mid-level**: invent suitable concepts/models for problems/theories
- **proof sketches**: explore stronger/related theories to get proof ideas
- **theory exploration**: develop interesting theories by conjecturing/proving
- **feedback loops**: (dis)prove, learn from it, (dis)prove more, learn more, ...
- **autoformalization**: (semi-)automate translation from LaTeX to formal
- ...

Large AI/TP Datasets

- Mizar / MML / MPTP – since 2003
- MPTP Challenge (2006), MPTP2078 (2011), Mizar40 (2013)
- Isabelle (and AFP) – since 2005
- Flyspeck (including core HOL Light and Multivariate) – since 2012
- HOL4 – since 2014, CakeML – 2017, GRUNGE – 2019
- Coq – since 2013/2016
- ACL2 – 2014?
- Lean?, Stacks?, Arxiv?, ProofWiki?, ...

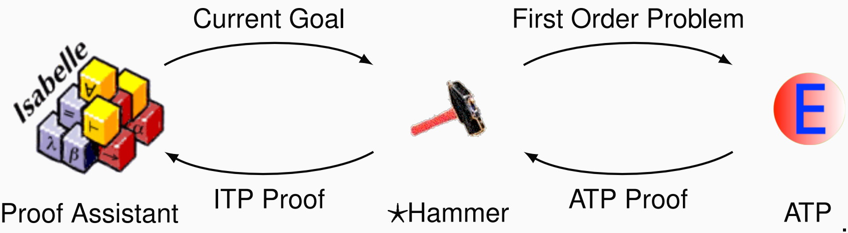
AI/TP Examples and Demos

- ENIGMA/hammer proofs of Pythagoras : `https://bit.ly/2MVPAn7` (more at `http://grid01.ciirc.cvut.cz/~mptp/enigma-ex.pdf`) and simplified Carmichael `https://bit.ly/3oGBdRz`,
- 3-phase ENIGMA: `https://bit.ly/3C0Lwa8`, `https://bit.ly/3BWqR6K`
- Long trig proof from 1k axioms: `https://bit.ly/2YZ0OgX`
- Extreme Deepire/AVATAR proof of $\epsilon_0 = \omega^{\omega^{\omega^{\cdot^{\cdot^{\cdot}}}}}$ `https://bit.ly/3Ne4WNX`
- Hammering demo: `http://grid01.ciirc.cvut.cz/~mptp/out4.ogv`
- TacticToe on HOL4: `http://grid01.ciirc.cvut.cz/~mptp/tactictoe_demo.ogv`
- Tactician for Coq: `https://blaauwbroek.eu/papers/cicm2020/demo.mp4`, `https://coq-tactician.github.io/demo.html`
- Inf2formal over HOL Light: `http://grid01.ciirc.cvut.cz/~mptp/demo.ogv`
- QSynt: AI rediscovers the Fermat primality test: `https://www.youtube.com/watch?v=24oejR9wsXs`

High-level ATP guidance: Premise Selection

- Early 2003: Can existing ATPs be used over the freshly translated Mizar library?
- About 80000 nontrivial math facts at that time – impossible to use them all
- Is good premise selection for proving a new conjecture possible at all?
- Or is it a mysterious power of mathematicians? (Penrose)
- Today: Premise selection is not a mysterious property of mathematicians!
- Reasonably good algorithms started to appear (more below).
- Extensive human (math) knowledge obsolete?? (cf. Watson, Debater, ..)
- Since 2004 (my PhD): many examples of nontrivial alternative proofs proposed by the AIs - in Mizar, Flyspeck, Isabelle, ..
- The premise selection algorithms see *wider* than humans

Today's AI-ATP systems (⋆-Hammers)



How much can it do?

- Mizar / MML – MizAR
- Isabelle (Auth, Jinja) – Sledgehammer
- Flyspeck (including core HOL Light and Multivariate) – HOL(y)Hammer
- HOL4 (Gauthier and Kaliszyk)
- CoqHammer (Czajka and Kaliszyk) - about 40% on Coq standard library

$\approx$ 40-45% success by 2016, 60% on Mizar as of 2021

Premise Selection and Hammer Methods

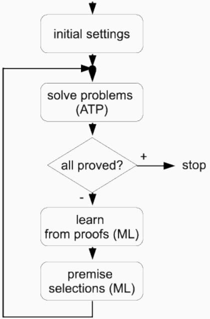
- Many syntactic features (symbols, walks in the parse trees)
- More semantic features encoding
- term matching/unification, validity in models, latent semantics (LSI)
- Distance-weighted k-nearest neighbor, SVMs, Naive Bayes
- Gradient boosted decision trees (GBDTs - XGBoost, LightGBM)
- Neural models: CNNs, RNNs/Attention/Transformers/GPT, GNNs
- As of 2020, tough competition between GBDTs, GNNs and RNNs/Transformers (and relatives)
- K-NN still very good, Olsak's logic-aware GNN probably best
- RNNs/Transformers good at stateful premise selection (Piotrowski 2019,2020)
- Ensemble methods combining the different predictors help a lot

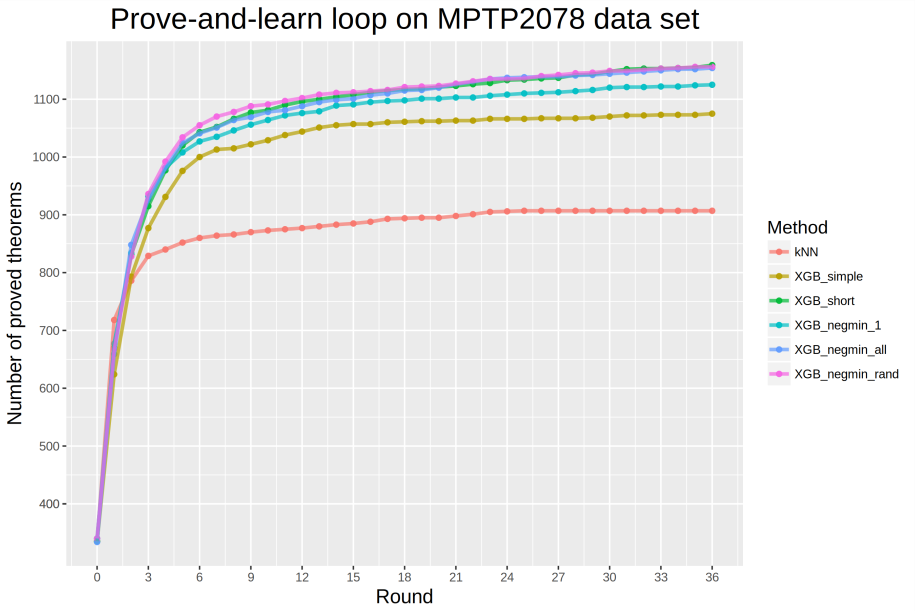
Premise Selection and Hammer Methods

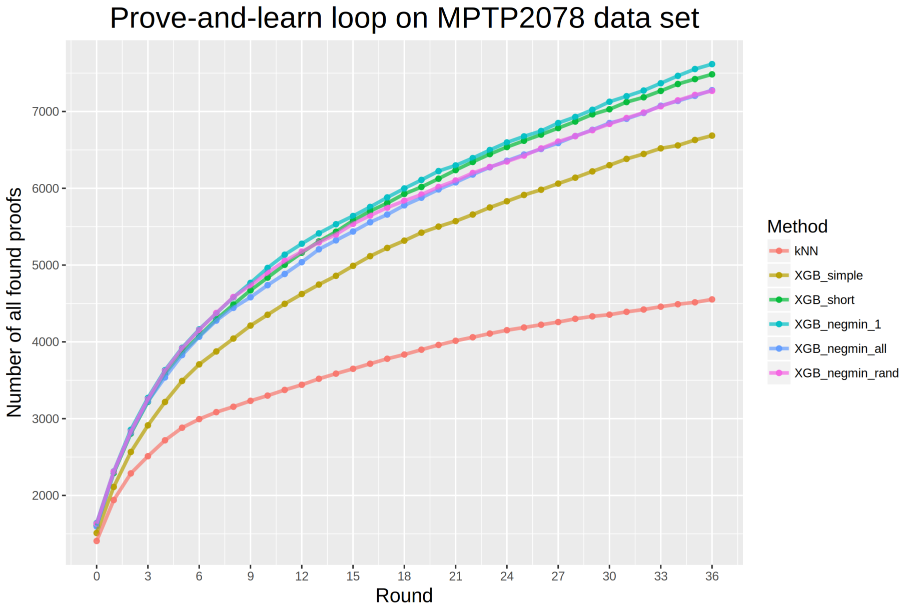
- Learning in a binary setting from many alternative proofs
- Interleaving many learning and proving runs (*MaLARea loop*) to get positives/negatives (ATPBoost - Piotrowski 2018)
- Matching and transferring concepts and theorems between libraries (Gauthier & Kaliszyk) – allows “superhammers”, conjecturing, and more
- Lemmatization – extracting and considering millions of low-level lemmas and learning from their proofs
- Hammers combined with guided tactical search: TacticToe (Gauthier - HOL4) and its later relatives

High-level feedback loops – MALARea, ATPBoost

- Machine Learner for Autom. Reasoning (2006) – infinite hammering
- feedback loop interleaving ATP with learning premise selection
- both syntactic and semantic features for characterizing formulas:
- evolving set of finite (counter)models in which formulas evaluated
- winning AI/ATP benchmarks (MPTPChallenge, CASC 2008/12/13/18)
- ATPBoost (Piotrowski) - recent incarnation focusing on multiple proofs

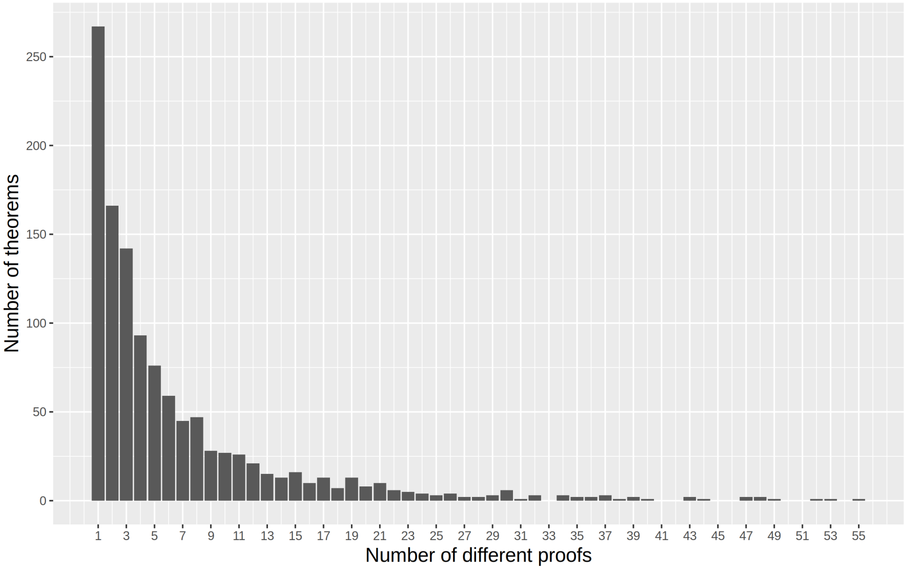



Prove-and-learn loop on MPTP2078 data set
Number of proved theorems
Round
1100
1000
900
800
700
600
500
400
0
3
6
9
12
15
18
21
24
27
30
33
36
Method
kNN
XGB_simple
XGB_short
XGB_negmin_1
XGB_negmin_all
XGB_negmin_rand



Prove-and-learn loop on MPTP2078 data set
Number of all found proofs
7000
6000
5000
4000
3000
2000
0
3
6
9
12
15
18
21
24
27
30
33
36
Round
Method
kNN
XGB_simple
XGB_short
XGB_negmin_1
XGB_negmin_all
XGB_negmin_rand

Number of found proofs per theorem at the end of the loop



Low-level: Statistical Guidance of Connection Tableau

- learn guidance of every clausal inference in connection tableau (leanCoP)
- set of first-order clauses, *extension* and *reduction* steps
- proof finished when all branches are closed
- a lot of nondeterminism, requires backtracking
- *Iterative deepening* used in leanCoP to ensure completeness
- good for learning – the tableau compactly represents the proof state

Clauses:

$c_1 : P(x)$

$c_2 : R(x, y) \vee \neg P(x) \vee Q(y)$

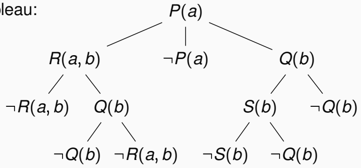
$c_3 : S(x) \vee \neg Q(b)$

$c_4 : \neg S(x) \vee \neg Q(x)$

$c_5 : \neg Q(x) \vee \neg R(a, x)$

$c_6 : \neg R(a, x) \vee Q(x)$

Closed Connection Tableau:



Statistical Guidance of Connection Tableau

- **MaLeCoP** (2011): first prototype Machine Learning Connection Prover
- extension rules chosen by naive Bayes trained on good decisions
- training examples: tableau features plus the name of the chosen clause
- initially slow: off-the-shelf learner 1000 times slower than raw leanCoP
- 20-time search shortening on the MPTP Challenge
- second version: 2015, with C. Kaliszyk
- both prover and naive Bayes in OCAML, fast indexing
- Fairly Efficient MaLeCoP = **FEMaLeCoP**
- 15% improvement over untrained leanCoP on the MPTP2078 problems
- using iterative deepening - enumerate shorter proofs before longer ones

Statistical Guidance of Connection Tableau – rlCoP

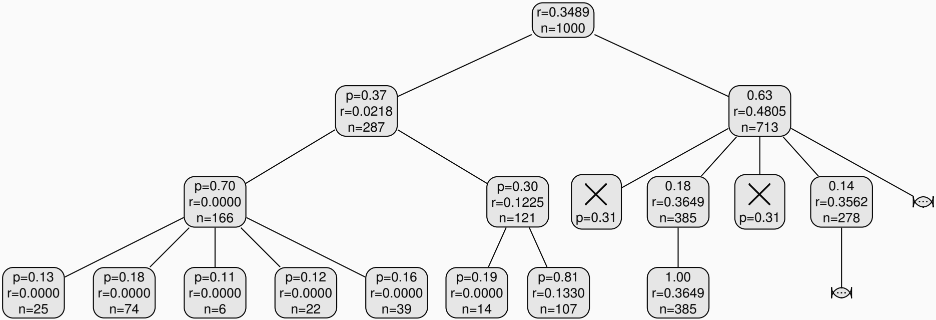
- 2018: stronger learners via C interface to OCAML (boosted trees)
- remove iterative deepening, the prover can go arbitrarily deep
- added Monte-Carlo Tree Search (MCTS)
- MCTS search nodes are sequences of clause application
- a good heuristic to explore new vs exploit good nodes:

$$\frac{w_i}{n_i} + c \cdot p_i \cdot \sqrt{\frac{\ln N}{n_i}}$$

(UCT - Kocsis, Szepesvari 2006)

- learning both *policy* (clause selection) and *value* (state evaluation)
- clauses represented not by names but also by features (generalize!)
- binary learning setting used: | proof state | clause features |
- mostly term walks of length 3 (trigrams), hashed into small integers
- many iterations of proving and learning

Tree Example



Statistical Guidance of Connection Tableau – rlCoP

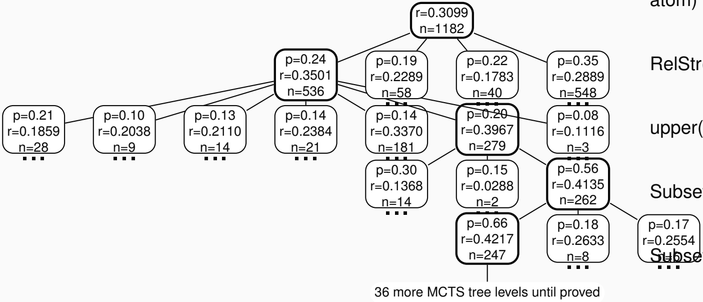
- On 32k Mizar40 problems using 200k inference limit
- nonlearning CoPs:

System	leanCoP	bare prover	rlCoP no policy/value (UCT only)
Training problems proved	10438	4184	7348
Testing problems proved	**1143**	431	804
Total problems proved	11581	4615	8152

- rlCoP with policy/value after 5 proving/learning iters on the training data
- $1624/1143 = 42.1$% improvement over leanCoP on the testing problems

Iteration	1	2	3	4	5	6	7	8
Training proved	12325	13749	14155	14363	14403	14431	14342	**14498**
Testing proved	1354	1519	1566	1595	**1624**	1586	1582	1591

More trees



(tableau starting atom)

RelStr(c1)

upper(c1)

Subset(union(c2),carrier(c1))

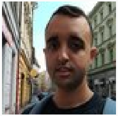
Subset(c2,powerset(carrier(c1)

Recent CoP Mutants: FLoP, GNN, RNN, lazyCoP

- FLoP – Finding Longer Proofs (Zombori et al, 2019)
- Curriculum Learning used for connection tableau over Robinson Arithmetic
- addition and multiplication learned perfectly from $1 * 1 = 1$
- headed towards learning algorithms/decision procedures from math data
- currently black-box, combinations with symbolic methods (ILP) our next target
- Using RNNs for better tableau encoding, prediction of actions ...
- ... even guessing (decoding) next tableau literals (Piotrowski 2020)
- plCoP (Zombori 20), GNN-CoP (Olsak 20), lazyCoP (Rawson)
- Zombori: learning new explainable Prolog actions (tactics) from proofs

ENIGMA (2017): Guiding the Best ATPs like E Prover

- ENIGMA (Jan Jakubuv, Zar Goertzel, Karel Chvalovsky, others)

- The proof state are two large heaps of clauses *processed*/*unprocessed*
- learn on E's proof search traces, put classifier in E
- positive examples: clauses (lemmas) used in the proof
- negative examples: clauses (lemmas) not used in the proof
- 2021 multi-phase architecture (combination of different methods):
  - fast gradient-boosted decision trees (GBDTs) used in 2 ways
  - fast logic-aware graph neural network (GNN - Olsak) run on a GPU server
  - logic-based subsumption using fast indexing (discrimination trees - Schulz)
- The GNN scores many clauses (context/query) together in a large graph
- Sparse - vastly more efficient than transformers (∼100k symbols)
- 2021: leapfrogging and Split&Merge:
- aiming at learning reasoning/algo components

Feedback prove/learn loop for ENIGMA on Mizar data

- Done on 57880 Mizar problems recently
- Serious ML-guidance breakthrough applied to the best ATPs
- Ultimately a 70% improvement over the original strategy in 2019
- From 14933 proofs to 25397 proofs (all 10s CPU - no cheating)
- Went up to 40k in more iterations and 60s time in 2020
- 75% of the Mizar corpus reached in July 2021 - higher times and many runs: `https://github.com/ai4reason/ATP_Proofs`

	$\mathcal{S}$	$\mathcal{S} \odot \mathcal{M}_9^0$	$\mathcal{S} \oplus \mathcal{M}_9^0$	$\mathcal{S} \odot \mathcal{M}_9^1$	$\mathcal{S} \oplus \mathcal{M}_9^1$	$\mathcal{S} \odot \mathcal{M}_9^2$	$\mathcal{S} \oplus \mathcal{M}_9^2$	$\mathcal{S} \odot \mathcal{M}_9^3$	$\mathcal{S} \oplus \mathcal{M}_9^3$
solved	**14933**	16574	20366	21564	22839	22413	23467	22910	23753
$\mathcal{S}\%$	+0%	+10.5%	+35.8%	+43.8%	+52.3%	+49.4%	+56.5%	+52.8%	+58.4
$\mathcal{S}+$	+0	+4364	+6215	+7774	+8414	+8407	+8964	+8822	+9274
$\mathcal{S}-$	-0	-2723	-782	-1143	-508	-927	-430	-845	-454

	$\mathcal{S} \odot \mathcal{M}_{12}^3$	$\mathcal{S} \oplus \mathcal{M}_{12}^3$	$\mathcal{S} \odot \mathcal{M}_{16}^3$	$\mathcal{S} \oplus \mathcal{M}_{16}^3$
solved	24159	24701	25100	**25397**
$\mathcal{S}\%$	+61.1%	+64.8%	+68.0%	**+70.0%**
$\mathcal{S}+$	+9761	+10063	+10476	+10647
$\mathcal{S}-$	-535	-295	-309	-183

ENIGMA Anonymous: Learning from patterns only

- The GNN and GBDTs only learn from formula structure, not symbols
- Not from symbols like $+$ and $*$ as Transformer & Co.
- E.g., learning on additive groups thus transfers to multiplicative groups
- Evaluation of old-Mizar ENIGMA on 242 new Mizar articles
- 13370 new theorems, $>$ 50% of them with new terminology:
- The 3-phase ENIGMA is **58%** better on them than unguided E
- While **53.5%** on the old Mizar (where this ENIGMA was trained)
- Generalizing, analogizing and transfer abilities unusual in the large transformer models

Neural Clause Selection in Vampire (M. Suda)

Deepire: Similar to ENIGMA:

- build a *classifier* for recognizing *good* clauses
- *good* are those that appeared in past proofs

Deepire's contributions:

- Learn from clause *derivation trees only*
  Not looking at what it says, just who its ancestors were.
- Integrate using *layered clause queues*
  A smooth improvement of the base clause selection strategy.
- Tree Neural Networks: constant work per derived clause
- A signature agnostic approach
- Delayed evaluation trick (not all derived need to be evaluated)

Preliminary Evaluation on Mizar "57880"

- Learn from 63595 proofs of 23071 problems (three 30s runs)
- Deepire solves 26217 (i.e. +4054) problems in a *single 10s run*

TacticToe: mid-level ITP Guidance (Gauthier'17,18)

- TTT learns from human and its own tactical HOL4 proofs
- No translation or reconstruction needed - native tactical proofs
- Fully integrated with HOL4 and easy to use
- Similar to rlCoP: policy/value learning for applying tactics in a state
- However much more technically challenging - a real breakthrough:
  - tactic and goal state recording
  - tactic argument abstraction
  - absolutization of tactic names
  - nontrivial evaluation issues
  - these issues have often more impact than adding better learners
- policy: which tactic/parameters to choose for a current goal?
- value: how likely is this proof state succeed?
- 66% of HOL4 toplevel proofs in 60s (better than a hammer!)
- similar recent work for Isabelle (Nagashima 2018), HOL Light (Google)

Tactician: Tactical Guidance for Coq (Blaauwbroek'20)

- Tactical guidance of Coq proofs
- Technically very challenging to do right - the Coq internals again nontrivial
- 39.3% on the Coq standard library, 56.7% in a union with CoqHammer (orthogonal)
- Fast approximate hashing for k-NN makes a lot of difference
- Speed more important than better learners
- Fully integrated with Coq, should work for any development
- User friendly, installation friendly, integration friendly and maintenance friendly
- Took several years, but could become a very common tool for Coq formalizers

Symbolic Rewriting with NNs

- Recurrent NNs with attention good at the inf2formal task
- Piotrowski 2018/19: Experiments with using RNNs for symbolic rewriting
- We can learn rewrite rules from sufficiently many data
- 80-90% success on AIM datasets, 70-99% on normalizing polynomials
- again, complements symbolic methods like ILP that suffer on big data
- in 2019 similar tasks taken up by Facebook - integration, etc.

Symbolic Rewriting Datasets

Table: Examples in the AIM data set.

Rewrite rule:	Before rewriting:	After rewriting:
`b(s(e,v1),e)=v1`	`k(b(s(e,v1),e),v0)`	`k(v1,v0)`
`o(V0,e)=V0`	`t(v0,o(v1,o(v2,e)))`	`t(v0,o(v1,v2))`

Table: Examples in the polynomial data set.

Before rewriting:	After rewriting:
`(x * (x + 1)) + 1`	`x ^ 2 + x + 1`
`(2 * y) + 1 + (y * y)`	`y ^ 2 + 2 * y + 1`
`(x + 2) * ((2 * x) + 1) + (y + 1)`	`2 * x ^ 2 + 5 * x + y + 3`

RL for Semantics-Aware Synthesis of Math Objects

- Gauthier'19-22:
- Tree Neural Nets and RL (MCTS, policy/value) for:
- Guiding normalization in Robinson arithmetic
- Guiding synthesis of combinators for a given lambda expression
- Guiding synthesis of a diophantine equation characterizing a given set
- Quite encouraging results with a good curriculum (LPAR, CICM)
- Motivated by his TacticToe: argument synthesis and conjecturing is the big missing piece
- Gauthier's deep RL framework verifies the whole series (proof) in HOL4
- 2022: OEIS invention from scratch - 50k sequences discovered:
  `https://www.youtube.com/watch?v=24oejR9wsXs`,
  `http://grid01.ciirc.cvut.cz/~thibault/qsynt.html`
- Many conjectures invented: 4 different characterizations of primes
- Non-neural (Turing complete) computing and semantics collaborates with the statistical learning

Prover9 - Research-Level Open Conjectures

- Michal Kinyon, Bob Veroff and Prover9: quasigroup and loop theory
- the Abelian Inner Mappinngs (AIM) Conjecture (>10 year program)
- Strong AIM: Q is AIM implies Q/Nuc(Q) is abelian and Q/Z(Q) is a group
- The Weak AIM Conjecture positively resolved in August 2021
- Q is AIM implies Q is nilpotent of class at most 3.
- 20-200k long proofs by Prover9 assisting the humans
- Prover9 hints strategy (Bob Veroff): extract hints from easier proofs to guide more difficult proofs
- Human-guided exploration to get good hints (not really automated yet)
- Millions of hints collected, various algorithms for their selection for a particular conjecture
- Symbolic machine learning?

RL of Neural Rewriting

- J. Piepenbrock (IJCAR'22): greatly improved RL for
- Gauthier's normalization in Robinson arithmetic
- Achieved good performance also on the polynomial normalization tasks
- Hold-out performance better than a top equational prover (Waldmeister) on AIM after 100 epochs of training on 2500 problems
- Combination with Prover9 outperforms also unguided Prover9
- Exciting: again, this is all in the verifiable/explainable proof format

METHOD	SUCCESS RATE ON AIM HOLD-OUT SET
WALDMEISTER (60S)	0.655
NEURALLY GUIDED REWRITING(60S)	0.702 ± 0.015
PROVER9 (2S)	0.746
E (60S)	0.802
PROVER9 (60S)	0.833
NEURALLY GUIDED REWRITING (1S) + PROVER9 (59S)	**0.902** $\pm$ 0.016

More on Conjecturing in Mathematics

- Targeted: generate intermediate lemmas (cuts) for a harder conjecture
- Unrestricted (theory exploration):
- Creation of interesting conjectures based on the previous theory
- One of the most interesting activities mathematicians do (how?)
- Higher-level AI/reasoning task - can we learn it?
- If so, we have solved math:
- ... just (recursively) divide Fermat into many subtasks ...
- ... and conquer (I mean: hammer) them away

A bit of conjecturing history

- The topic goes back at least to Lenat (AM) and Fajtlowicz (Graffiti)
- Combined with automated theorem proving by Colton et al. in early 2000s (HR)
- Theory exploration for Isabelle by Johansson et al (Hipster)
- Several learning-based/neural approaches by our groups since 2015:
- Based mainly on learning analogies and informalization followed by probabilistic/neural disambiguation ...
- ... Gauthier, Kaliszyk, Chvalovsky, Piotrowski, Goertzel, Wang, Brown, JU

Conjecturing and Proof Synthesis by Neural Language models

- Karpathy’15 - RNN experiments with generating fake Math over Stacks
- I have tried to use that for formal math in 2016 but it looked weak
- GPT (-2,3) looks stronger
- Renewed experiments in 2020 on:
- All Mizar articles, stripped of comments and concatenated together (78M)
- Articles with added context/disambiguation (156M) (types, names, thesis)
- TPTP proofs of 28271 Mizar/MPTP theorems by E/ENIGMA (658M)
- Just the conjecture and premises needed for the 28271 proofs printed in prefix notation
- Quite interesting results, server for Mizar authors
- Quickly taken up by others on HOL, Isabelle, MetaMath ...

Can you find the flaw(s) in this fake GPT-2 proof?

```
:: generated theorem with "proof"
theorem Th23: :: STIRL2_1:23
for X, Y being finite set st not X is empty & X c= Y
& card X = card Y holds X = Y
proof
  let X, Y be finite set ;
:: thesis: not X is empty & X c= Y & card X = card Y implies X = Y
  assume that
  A1: not X is empty and A2: X c= Y and A3: card X = card Y ;
:: thesis: X = Y
  card (Y \ X) = (card Y) - (card X) by A1, A3, CARD_2:44;
  then A4: card (Y \ X) = ((card Y) - 1) - (card X) by CARD_1:30;
  X = Y \ X by A2, A3, Th22;
  hence X = Y by A4, XBOOLE_0:def_10;
:: thesis: verum
end;
```

-:--- card_tst.miz   99% L2131 (Mizar Errors:13 hs Undo-Tree)

Figure: Fake full declarative GPT-2 “proof” - typechecks!

Mizar autocompletion server in action

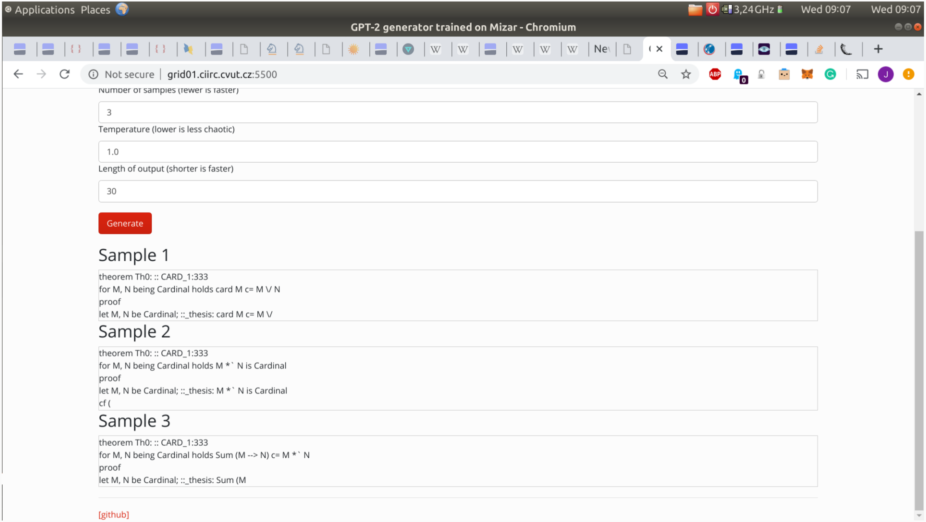


Figure: MGG - Mizar Gibberish Generator.

Proving the conditioned completions - MizAR hammer

Applications Places   4,81 GHz   Wed 14:42   Wed 14:42

emacs@dell

File Edit Options Buffers Tools Index Mizar Hide/Show Help

Save Undo

```
begin

for M, N being Cardinal holds card M c= M \/ N by XBOOLE_1:7,CARD_3:44,CARD_1:7,CARD_1:3; :: [ATP details]

for X, Y being finite set st not X is empty & X c= Y & card X = card Y holds X = Y by CARD_FIN:1; :: [ATP details]

for M, N being Cardinal holds
( M in N iff card M c= N ) by Unsolved; :: [ATP details]

for M, N being Cardinal holds
( M in N iff card M in N ) by CARD_3:44,CARD_1:9; :: [ATP details]

for M, N being Cardinal holds Sum (M --> N) = M *` N by CARD_2:65; :: [ATP details]


for M, N being Cardinal holds M /\ (union N) in N by Unsolved; :: [ATP details]


for M, N being Cardinal holds M *` N = N *` M by ATP-Unsolved; :: [ATP details]
```

-:--- **card_tst.miz**   3% L47   (Mizar Errors:2 hs Undo-Tree)

Wrote /home/urban/mizwrk/7.13.01_4.181.1147/tst8/card_tst.miz

A correct conjecture that was too hard to prove

- Kinyon and Stanovsky (algebraists) confirmed that this cut is valid:

```
theorem Th10: :: GROUPP_1:10
for G being finite Group for N being normal Subgroup of G st
N is Subgroup of center G & G ./. N is cyclic holds G is commutative

The generalization that avoids finiteness:

for G being Group for N being normal Subgroup of G st
N is Subgroup of center G & G ./. N is cyclic holds G is commutative
```

Gibberish Generator Provoking Algebraists

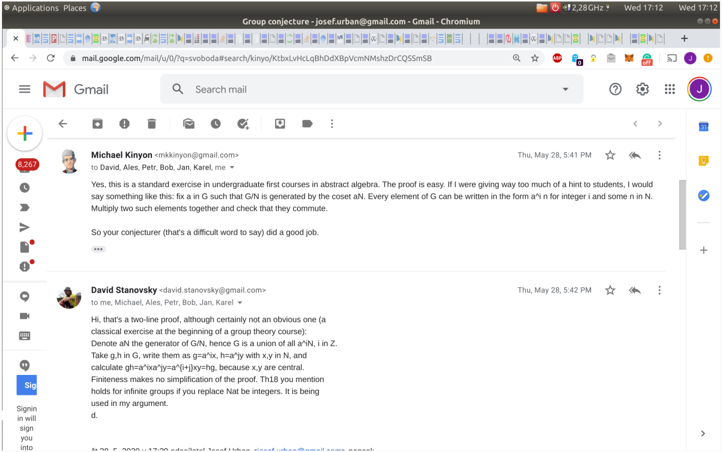


Figure: First successes in making mathematicians comment on AI.

More cuts

- In total 33100 in this experiment
- Ca 9k proved by trained ENIGMA
- Some are clearly false, yet quite natural to ask:

```
theorem :: SINCOS10:17

sec is increasing on [0, pi/2)
```

leads to conjecturing the following:

```
Every differentiable function is increasing.
```

Neural Autoformalization (Wang et al., 2018)

- generate ca 1M Latex/Mizar pairs based on Bancerek's work
- train neural seq-to-seq translation models (Luong – NMT)
- evaluate on about 100k examples
- many architectures tested, some work much better than others
- very important latest invention: *attention* in the seq-to-seq models
- more data very important for neural training – our biggest bottleneck (you can help!)
- Recent addition: unsupervised methods (Lample et all 2018) – no need for aligned data!

Neural Autoformalization data

Rendered LaTeX	If $X \subseteq Y \subseteq Z$, then $X \subseteq Z$.
Mizar	`X c= Y & Y c= Z implies X c= Z;`
Tokenized Mizar	`X c= Y & Y c= Z implies X c= Z ;`
LaTeX	`If $X \subseteq Y \subseteq Z$, then $X \subseteq Z$.`
Tokenized LaTeX	`If $ X \subseteq Y \subseteq Z $ , then $ X \subseteq Z $ .`

Neural Autoformalization results

Parameter	Final Test Perplexity	Final Test BLEU	Identical Statements (%)	Identical No-overlap (%)
128 Units	3.06	41.1	40121 (38.12%)	6458 (13.43%)
256 Units	1.59	64.2	63433 (60.27%)	19685 (40.92%)
512 Units	1.6	**67.9**	66361 (63.05%)	21506 (44.71%)
1024 Units	**1.51**	61.6	**69179 (65.73%)**	**22978 (47.77%)**
2048 Units	2.02	60	59637 (56.66%)	16284 (33.85%)

Neural Fun – Performance after Some Training

Rendered LaTeX	Suppose s_8 is convergent and s_7 is convergent . Then $\lim(s_8+s_7) = \lim s_8 + \lim s_7$
Input LaTeX	`Suppose $ { s _ { 8 } } $ is convergent and $ { s _ { 7 } } $ is convergent . Then $ \mathop { \rm lim } ( { s _ { 8 } } { + } { s _ { 7 } } } ) \mathrel { = } \mathop { \rm lim } { s _ { 8 } } { + } \mathop { \rm lim } { s _ { 7 } } $ .`
Correct	`seq1 is convergent & seq2 is convergent implies lim ( seq1 + seq2 ) = ( lim seq1 ) + ( lim seq2 ) ;`
Snapshot-1000	`x in dom f implies ( x * y ) * ( f | ( x | ( y | ( y | y ) ) ) ) = ( x | ( y | ( y | ( y | y ) ) ) ) ) ;`
Snapshot-2000	`seq is summable implies seq is summable ;`
Snapshot-3000	`seq is convergent & lim seq = 0c implies seq = seq ;`
Snapshot-4000	`seq is convergent & lim seq = lim seq implies seq1 + seq2 is convergent ;`
Snapshot-5000	`seq1 is convergent & lim seq2 = lim seq2 implies lim_inf seq1 = lim_inf seq2 ;`
Snapshot-6000	`seq is convergent & lim seq = lim seq implies seq1 + seq2 is convergent ;`
Snapshot-7000	`seq is convergent & seq9 is convergent implies lim ( seq + seq9 ) = ( lim seq ) + ( lim seq9 ) ;`

Unsupervised NMT Fun on Short Formulas

`len <* a *> = 1 ;`	`len <* a *> = 1 ;`
`assume i < len q ;`	`i < len q ;`
`len <* q *> = 1 ;`	`len <* q *> = 1 ;`
`s = apply ( v2 , v1 ast t ) ;`	`s = apply ( v2 , v1 ) . t ;`
`s . ( i + 1 ) = tt . ( i + 1 )`	`s . ( i + 1 ) = tau1 . ( i + 1 )`
`1 + j <= len v2 ;`	`1 + j <= len v2 ;`
`1 + j + 0 <= len v2 + 1 ;`	`1 + j + 0 <= len v2 + 1 ;`
`let i be Nat ;`	`i is_at_least_length_of p ;`
`assume v is_applicable_to t ;`	`not v is applicable ;`
`let t be type of T ;`	`t is_orientedpath_of v1 , v2 , T ;`
`a ast t in downarrow t ;`	`a *' in downarrow t ;`
`t9 in types a ;`	`t '2 in types a ;`
`a ast t <= t ;`	`a *' <= t ;`
`A is_applicable_to t ;`	`A is applicable ;`
`Carrier ( f ) c= B`	`support ppf n c= B`
`u in B or u in { v } ;`	`u in B or u in { v } ;`
`F . w in w & F . w in I ;`	`F . w in F & F . w in I ;`
`GG . y in rng HH ;`	`G0 . y in rng ( H1 ./. y ) ;`
`a * L = Z_ZeroLC ( V ) ;`	`a * L = ZeroLC ( V ) ;`
`not u in { v } ;`	`u >> v ;`
`u <> v ;`	`u <> v ;`
`v - w = v1 - w1 ;`	`vw = v1 - w1 ;`
`v + w = v1 + w1 ;`	`v + w = v1 + w1 ;`
`x in A & y in A ;`	`assume [ x , y ] in A ;`

Future: AITP Challenges/Bets from 2014

- 3 AITP bets from my 2014 talk at Institut Henri Poincare
  - In 20 years, 80% of Mizar and Flyspeck toplevel theorems will be provable automatically (same hardware, same libraries as in 2014 - about 40% then)
  - In 10 years: 60% (DONE already in 2021 - 3 years ahead of schedule)
  - In 25 years, 50% of the toplevel statements in LaTeX-written Msc-level math curriculum textbooks will be parsed automatically and with correct formal semantics (this may be faster than I expected)
- My (conservative?) estimate when we will do Fermat:
  - Human-assisted formalization: by 2050
  - Fully automated proof (hard to define precisely): by 2070
  - See the Foundation of Math thread: `https://bit.ly/300k9Pm`
- Big challenge: Learn complicated symbolic algorithms (not black box)

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- HOL(y)Hammer group in Innsbruck:
  - Cezary Kaliszyk, Thibault Gauthier, Michael Faerber, Yutaka Nagashima, Shawn Wang
- ATP and ITP people:
  - Stephan Schulz, Geoff Sutcliffe, Andrej Voronkov, Kostya Korovin, Larry Paulson, Jasmin Blanchette, John Harrison, Tom Hales, Tobias Nipkow, Andrzej Trybulec, Piotr Rudnicki, Adam Pease, ...
- Learning2Reason people at Radboud University Nijmegen:
  - Herman Geuvers, Tom Heskes, Daniel Kuehlwein, Evgeni Tsivtsivadze, ...
- Google Research: Christian Szegedy, Geoffrey Irving, Alex Alemi, Francois Chollet, Sarah Loos
- ... and many more ...
- Funding: Marie-Curie, NWO, ERC

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Thanks and Advertisement

- Thanks for your attention!
- AITP – Artificial Intelligence and Theorem Proving
- September 4–9, 2022, Aussois, France, `aitp-conference.org`
- ATP/ITP/Math vs AI/Machine-Learning people, Computational linguists
- Discussion-oriented and experimental
- Grown to 80 people in 2019
- Will be hybrid in 2022 as in 2021 and 2020