

Fuchs (1995) – heuristic learned to be chosen with Gen Algo

Denzinger and Schulz (1996) – inference control heuristics for equational deduction. Data from prev proofs, select equations that are likely to be used in new situations. 1st eval fn works by symbolic retrieval of generalized patterns from a knn base, 2nd eval fn compiles the knowledge into abstract term evaluation trees. **Analyzed proof protocols** by representing knowledge about protocols’n’proofs

Denzinger et al. (1997) – case-based reasoning, similarity concept, cooperation concept, reactive planning; still ‘learn’ from previous successful proof attempts’

Fuchs (1998) – Learn search-guiding heuristics by employing features in a simple, yet effective manner. Features used to adapt a heuristic to a solved problem. Utilize heuristic profitably for related target problems. **Prediction of usefulness of a fact.**

SNoW Carlsson et al. (1999) – learning program that can be used as a general purpose multi-class classifier and is specifically tailored for large number of features. Sparse Network of Winnows (not a typo). Sparse network of sparse linear functions over a pre-defined or incrementally acquired feature space. Several update rules may be used – sparse variations of the Winnow update rule, the Perceptron or Naive Bayes. Multi class learner. Decisions either binary or continuous (confidence in  $[0, 1]$ ).

Proof General Aspinall (2000) – tool for developing proofs with ITP. Interaction based around proof script (seq of commands sent to ITP). Provides UI.

Mizar proof advisor Urban (2004) – MPTP (Mizar Problems for Theorem Proving) is system described; translates MML into FOL for ATPs and for generating thm proving problems corresponding to Mizar Mathematical Library. Mizar proof advisor used for selecting suitable axioms from the large library for an arbitrary problem. Feature based ML framework, symbols are the features that characterise formulas. They had 40k targets and about 7k features. **SNoW** learning architecture used mainly (NLP archit, designed for large num of feat and targets).

MizarMode Urban (2006) – Emacs authoring environment. Code-generating Code-Browsing Code-searching methods. Auto gen proof skeletons, semantic browsing of articles, structured viewing, proof advice using **machine learning tools** like Mizar Proof Advisor.

Lightweight relevance filtering ... Meng and Paulson (2009) – relevance filtering methods, based on counting fn symbols in clauses. Signature based relevance filter. Not exactly ML?...

The use of Data-Mining... Duncan (2007) – evaluate the applicability of data-mining techniques for tactics from large corpuses of proofs. Data mine information to find occurring patterns. Patterns are then evolved into tactics. Variable Length Markov Models used to predict next proof step.

MaLARea Urban (2007) – simple metasystem iteratively combining deductive Automated Reasoning tools (now the E and the SPASS ATP systems) with a machine learning component (now the SNoW system used in the naive

Bayesian learning mode). Intended use – large theories, i.e. large num of problems which in a consistent fashion use many axioms, lemmas, thms, etc. The system works in cycles of thm proving followed by ML from successful proofs, using the learned information to prune the set of available axioms for the next cycle. MPTP challenge - 142/252. Learning could be stated as creating an assoc of some features of the conjecture with proving methods. Features – just symbols appearing in them. "Proving method" – ordering of all av axioms. Goal – given symbols, produces ordering of axioms, according to expected relevancy wrt the set of symbols. Sufficiently simple to implement and quite efficient in the first experiments with thm proving over Mizar library. Deduce, learn, loop implemented via growing axiom set and growing timelimit policy. First try to solve cheaply (min num axioms / most relevant, lowest timelimit). On success, learning performed on the newly available solution and axiom/time limit dropped to min values. No success – increase limits. Details in paper. MLMLMLMLML SNoW used in NB mode, bcs of speed. One training example contains all the symbols of a solved conjecture w/ names of axioms needed. A bayes network is trained. Easier to just relearn every time. Trained classifier is used to prune the axiom set for the next runs – we take all the unsolved conjectures and create a testing example from each by taking all its symbols. The classifier run on this printing (ordered) axioms. This is then used to select req num of axioms. Usage of previous results exists.

SRASS Sutcliffe and Puzis (2007) – selection determined by semantics of the axioms and conjecture, heuristically ordered by a syntactic relevance measure. Many problems more solved. At each iter the process looks for a model of selected axioms and the neg of the conjecture. If no model found, then the conjecture is consequence. Otherwise, then an unselected axiom that is false in the model is moved to the set of selected axioms. Newly selected axiom excludes the model from the models of the selected axioms and neg conj, eventually leading to a situation where there are no models of the selected axioms and the negated conjecture. Unselected axioms selected in decreasing order of usefulness. Syntactic relevance score for usefulness. Direct relevance is ratio of how many predicates and/or functors they have in common to how many they have overall. Contextual direct relevance uses 'contextual intersection'.

MaLAREa SG Urban et al. (2008) – combines model-based and learning based methods for automated reasoning in large theories. The implementation is based on MaLAREa. Extended by taking into account semantic relevance of axioms, similar to SRASS. Combined system outperforms both. Three extensions to selection of axioms. 1. check for countersatisfiability in runs where this is probable. Allows for countersatisfiability precheck to detect more cases when more axioms need to be added. 2. Use models found when a problem is found to be countersatisfiable, as an additional criterion for computing axiom relevance. Need to efficiently evaluate formulae in the models. 3. Extend axiom specification using a logical criterion: the set of axioms should exclude as many known models of the negated conjecture as possible. **Weird combination. Review!**

MaLeCoP Urban et al. (2011) – TABLEAU CALCULUS YAY!!! While in

MaLARea learning-based axiom selection is done outside unmodified theorem provers, in MaLeCoP the learning-based selection is done inside the prover, and the interaction between learning of knowledge and its application can be much finer. The general design that we propose is as follows (see also Figure 1): The theorem prover (P) should have a sufficiently fast communication channel to a general advisor (A) that accepts queries (proof state descriptions) and training data (characterization of the proof state together with solutions and failures) from the prover, processes them, and replies to the prover (advising, e.g., which clauses to choose). The advisor A also talks to external system(s) (E). A translates the queries and information produced by P to the formalism used by a particular E, and translates E's guidance back to the formalism used by P. At suitable time, A also hands over the (suitably transformed) training data to E, so that E can update its knowledge of the world on which its advice is based. A is free to spawn/query as many instances/versions of E's as necessary, and A is responsible for managing the guidance provided by them. Particular instances of E's that we have in mind are learning systems, however we believe that the tableau setting is also suitable for linking of SMT solvers, computer algebra systems, and all kinds of other AI systems, probably in a more straightforward way than for the resolution-based systems. SNoW again...

Premise selection .. and kernel methods Alama et al. (2011) – This work develops learning-based premise selection in two ways. First, a newly available minimal dependency analysis of existing high-level formal mathematical proofs is used to build a large knowledge base of proof dependencies, providing precise data for ATP-based re-verification and for training premise selection algorithms. Second, a new machine learning algorithm for premise selection based on kernel methods is proposed and implemented (Section 4 gives details) 0/1 features if sth appears in conjecture. Looking for a classifier fn which, given a conjecture c, estimates how useful p is for proving c. (still the aproach with chosing the best some premises) Maths explained nicely.

Flyspeck Kaliszyk and Urban (2014) – Trained on Flyspeck proofs. (HOL Light is an ITP) The procedure implemented for HOLLight is currently a combination of the external, internal, learning, and non-learning premise selection approaches. This procedure assumes the common ITP situations of a large library of (also definitional) theorems  $T_i$  and their proofs  $P_i$  (for definitions the proof is empty). The proofs refer to other theorems giving rise to a partial ordering of thms etended into their total chrono order. Procedure:

1. characterisations of thms and proofs are extracted in a simple format
2. dependency data are obtained by running ATPs on the ATP problems created from the hollight deps, i.e. tms are re-proved. Preferred (it is smaller) data. Exported as 1
3. external premise selectors preprocess the thm characterizations and the proof deps. Multiple characterizations and proof dependencies may be used

4. when an new conjecture is stated in hollight its characterization is extracted and sent to the pretrained first stage premise selectors.
5. the first stage premise selectors work as rankers. For a given conjecture characterization they produce a ranking of the available theorems (premises) according to their (assumed) relevance for the conjecture.
6. The best ranked premises are used inside hollight to produce atp problems. Several thresholds on num of included premises are used, resulting in multiple versions of the ATP problems.
7. The ATPs are called on the problems. Some of the best ATPs run in a strategy-scheduling mode combining multiple strategies. Some of the strategies always use the SInE (i.e. local, second stage) premise selection (with different parameters) and some other strategies may to use SINE when the ATP problem is sufficiently large.

### ML of Premise Selection

All the currently used first-stage premise selectors are machine learning algorithms trained in various ways on previous proofs. A number of machine learning algorithms can be experimented with today, and in particular kernel-based methods and ensemble methods have recently shown quite good performance on smaller datasets such as MPTP2078. Scaling hard on large corpus. So far this work uses mostly sparse implementation of a multiclass NB classifier (SNoW again...). Several other fast incremental learning algorithms were briefly tried – perceptron and winnow algos (SNoW) and custom k-NN. Only k-NN produced enough additional prediction power.

At a given point during the library development, the training data available to the machine learners are the proofs of the previously proved theorems in the library. A frequently used approach to training premise selection is to characterize each proof  $P_i$  of theorem  $T_i$  as a (multi)set of theorems  $\{T_{i_1}, \dots, T_{i_m} | T_{i_j} \text{ used in } P_i\}$ . The training example will consist of the input characterization (features) of  $T_i$  (features) and the output characterization of  $T_i$  (labels) will be the multi set  $\{T_i\}$  and the previous set. Such training examples can be tuned in various ways. For example the output theorems may be further recursively expanded with their own dependencies, the input features could be expanded with the features of their definitions, various weighting schemes and similarity clusterings can be tried, etc. This is also mostly left to future general research in premise-selection learning. Once the machine learner is trained on a particular development state of the library, it is tested on the next theorem  $T$  in the chronological order. The input features are extracted from  $T$  and given to the trained learner which then answers with a ranking of the available theorems. This ranking is given to HOL Light, which uses it to produce ATP problems for  $T$  with varied numbers of the best-ranked premise

Stronger automation for Flyspeck... Kaliszyk and Urban (2013) – 2 complementary AI methods used to improve strength of ai/atp service. First, several schemes for frequency-based feature weighting are explored in combination

with distance-weighted k-nearest-neighbor classifier. A smaller improvement is obtained by evolving targeted E prover strategies on two particular premise selections, using the Blind Strategymaker (BliStr) system. (FOR THE PREVIOUS) custom implementation of the k-nearest neighbor (k-NN) machine-learning method, which computes for a new example (conjecture) the k nearest (in a given feature distance) previous examples and ranks premises by their frequency in these examples. (

END) The simplest way how to measure the similarity of formulas to the new conjecture is to compute the overlap of their (sparse) feature vectors. Neglected by our first implementation is however the sensitivity of k-NN to feature frequencies. Inverse Document Frequency weighting.

MaSh Kühlwein et al. (2013) – Sledgehammer had relevance filter (syntactic similarity). Mash learns from successful proofs. Integrates easily. *Draws on recent research in the context of Mizar and HOL Light*. CUSTOM version of a weighted sparse naiveB algo, that is faster than the NB in SNoW. Maintains persistent state and supports incremental, nonmonotonic updates. The main technical difficulty is to perform the learning in a fast and robust way without interfering with other activities of the proof assistant. Power users can enhance the learning by letting external provers run for hours on libraries, searching for simpler proofs. A particularly strong filter, MeSh, is obtained by combining MePo (MEPO is paulsons thingie which selects based on num of relevant symbols) and MaSh. Implementations refines this in several ways – chained facts take absolute priority, local facts are preferred to global, first order facts preferred to hol ones; rare symbols are weighted more heavily; etc. Mepo tends to perform best on that contain some rare symbols, otherwise it discriminates poorly. There is also issue of starvation: the filter with its iterative expansion of the set of relevant symbols effectively performs a best first search and may ignore some relevant facts close to the root. Provers given ranked selected facts. Time limit and number of facts vary (the classic setting). Once a proof is found, Sledgehammer minimizes it by invoking the prover repeatedly with subsets of the facts it refers to.

### The ML engine

Default algorithm NB adapted to fact selection. Manipulates thm proving concepts in an abstract way. Handcrafted features. Sources of proofs – all facts in theories. Most interesting lemmas, those written by man. (see paper for math details)

MaLAREa04 Kaliszyk et al. (2014) – seems like nothing new...

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