



# Machine Learning for Theorem Proving Lecture 2 (VU)

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### Overview

#### Last Lecture

- Theorem Proving Overview
- Proof Assistants
- Comparison with other tools

#### Today

- Mini-rehearsal on machine learning
- Machine Learning problems in proving
- Lemma selection
- Statistical methods

# Summary of Last Lecture

- Proofs in mathematics and computer are getting more complex
  - some of them are beyond humans to verify
  - rare in mathematics, but more common for large software
- This increases the attractivity of proof assistants. Definition:
  - a computer program to assist a mathematician
    - (how: keep track of theories, definitions, assumptions, check individual steps, provide decision procedures)
  - in the production of a proof
  - that is mechanically checked
    - (means: completely verifiable in a formal logical system)
- Human work: translate human proof accurately and fill in gaps
  - Automation/ATPs help!
- Can machine learning help in this process?

### Homework

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• What are their specifics?

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#### Specify one LICS exercise in TPTP

- Can an automated prover solve it?
- Compare the number of useful/unused inferences/proof size

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#### Specify one LICS exercise in TPTP

- Can an automated prover solve it?
- Compare the number of useful/unused inferences/proof size

#### Specify it in an interactive theorem prover

Can you perform any natural-deduction like inference step?

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#### Algorithms that improve their performance based on data

- Face detection
- Recommender systems
- Speech recognition
- Stock prediction
- Spam detection
- Molecule modeling
- Automated translation
- LLMs ...

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#### ML Tasks

- Classification
- Regression
- Clustering
- Density Estimation
- Dimensionality Reduction

# Tasks related to proofs and reasoning

#### Tasks involving logical inference

- Natural language question answering
- Knowledge base completion
- Automated translation

#### Games

AlphaGo (Zero) problems similar to proving

- Node evaluation
- Policy decisions

[Sukhbaatar+2015]

[Socher+2013]

[Wu+2016]

[Silver+2016]

### Problems

#### Main machine learning problems

- Regression: estimate a parameter (1 function)
- Classification: estimate a class (point in plane, digit)
- Clustering

#### **Correspond to**

- Supervised learning
- Unsupervised learning
- ...

# AI theorem proving techniques (1/3)

#### **High-level AI guidance**

- Problems where machine learning helps predict and suggest actions that a human selects
- First such problem is **premise selection**: given a statement that we are trying to prove and a very large library of facts, find the parts of the knowledge that are most useful. For example if we have a fact that looks like topology, a human can find books on topology in a library. A machine learning algorithm can process thousands of books and facts in them can it select the most useful ones for our goal?
- Second such problem is **tactic selection**: again given a conjecture we have a number of known proof techniques. Predicting that a particular statement should be proved by induction, or for example by integration by parts is a task that a machine learning system could be trained on.
- For both these tasks we need a sufficiently good **characterization** of the goals, proof states, lemmas etc. As such it is necessary to find suitable features and learning techniques. And gather sufficient learning **data**.
- We often have 5–10 seconds to perform the actual prediction, with more the human will likely do better.

# AI theorem proving techniques (2/3)

#### **Mid-level AI guidance**

- Problems where the learning can select a strategy for an automated prover, for a tactic, choose a heuristic
- Selecting lemmas that can be reused, proposing intermediate lemmas
- Suggesting new conjectures
- We often have 0.1–3 seconds to perform the actual prediction, with more time running a tool for longer will likely do better human will likely do better.

# AI theorem proving techniques (3/3)

#### Low-level AI guidance

- Al can also be used to directly guide the actions of an automated theorem prover
- This means selecting (almost) every inference step by previous knowledge
- Depending on a calculus this may mean hundreds to tens of thousands of inferences per second
- In some ATPs this may be the selection of a clause to expand, in some ATPs this may be the selection of substitutions to apply, in some cases a branch etc.
- In order to make very fast decisions it is necessary to have very good proof-state characterizations and fast relevance: typically minimal statistical methods
- Most recently also decision tree -based predictions, despite slowing the prover down 2-5 times can allow having overall higher performance

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- What should the next proof step be?
  - Tactic? Instantiation?
- What new problem is likely to be true?
  - Intermediate statement for a conjecture

### Premise selection

#### Intuition

Given:

- set of theorems *T* (together with proofs)
- conjecture *c*

Find: minimal subset of T that can be used to prove c

#### More formally

$$\arg\min_{t\subseteq T}\{|t|\mid t\vdash c\}$$

(or  $\emptyset$  if not provable)

Note: implicit assumption on a proving system. ATP in practice.

# In machine learning terminology

#### **Multi-label classification**

Input: set of samples S, where samples are triples s, F(s), L(s)

- s is the sample ID
- *F*(*s*) is the set of features of *s*
- *L*(*s*) is the set of labels of *s*

**Output**: function f : features  $\rightarrow$  labels

Predicts *n* labels (sorted by relevance) for set of features

#### Sample features

Sample add\_comm (a + b = b + a) characterized by:

- F(add\_comm) = {"+", "=", "num"}
- L(add\_comm) = {num\_induct, add\_0, add\_suc, add\_def}

Labels correspond to premises and samples to theorems

• Very often same, a theorem is usually proved so it is both something that can be predicted and is a label of a training example. If *a* is proved using *b* and *b* is proved using *c* should we predict *c* for *a* as well? Should we predict *a* for *a* itself?

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Temporal order

• Recently considered theorems and premises are important (also in evaluation)

# Not exactly for the usual machine learning tools

#### Needs efficient learning and prediction

- Frequent major data updates: Whenever a user changes some definition or statement does it mean we have to relearn everything?
- Automation cannot wait more than 10 seconds
- Often less, the user / reasoning can do more in that time...

#### **Multi-label classifier output**

- Often asked for thousands of most relevant lemmas
- Most tools do 3–10

#### Easy to get many interesting features

- Complicated feature relations
- Both linguistic techniques and feature space reduction: PCA / LSA / ...?

# Additional Literature (not required)

The paper describes a number of learning problems on a particular dataset.

 Cezary Kaliszyk, François Chollet, and Christian Szegedy.
Holstep: A machine learning dataset for higher-order logic theorem proving.
In 5th International Conference on Learning Representations, ICLR 2017, Toulon, France, April 24-26, 2017, Conference Track Proceedings. OpenReview.net, 2017.

# Summary

#### **This Lecture**

- Machine Learning problems
- Lemma selection

#### Next

- k-nearest neighbours and naive Bayes classifiers
- other statistical methods
- kernels
- decision trees
- random forests

# Work Here / Homework

#### Find a large interactive proof

- Present an outline
- Try to characterize the main statement and its main premises
- Apply the ML problems to this informally (e.g. where to search main premises, main proof techniques, ...)

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#### Find a large automated proof

- Discuss main technique
- Which ML problems are applicable to shorten / speed up the proof?