

Useful Lemmas in E ATP Proofs

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Outline of talk

- **What are lemmas and why do they matter?**
- **Quantifying lemma usefulness.**
- **Machine learning to identify lemmas.**
- **Conclusion.**

Lemmas

Lemmas are:

- **True statements**
- **Intermediate results**
- **Sometimes used in multiple theorems**

Why seek lemmas?

- **ATPs struggle to find long proofs.**
- **Conjecturing new (interesting) results.**
- **Concise presentations of proofs.**

Lemmas as Cuts

Given axiom set Γ and conjecture C , we want to prove $\Gamma \vdash C$.

We call L a lemma if the following holds:

$$\frac{\Gamma \vdash L \quad \Gamma, L \vdash C}{\Gamma \vdash C}$$

* This doesn't require L be a "useful lemma".

Lemmas via Excluded Middle

E is a refutational theorem prover and tries to derive a contradiction: $\Gamma, \neg C \vdash \perp$.

Therefore the problem can be broken into two sub-problems:

$$\frac{\Gamma, L \vdash C \quad \Gamma, \neg L \vdash C}{\Gamma, (L \vee \neg L) \vdash C}$$

Lemma Usefulness: Proof Shortening Ratio

$$psr(L, \Gamma, C) = \frac{|\Gamma, L \vdash C| + |\Gamma, \neg L \vdash C|}{|\Gamma \vdash C|}$$

If the two sub-problems can be solved (by E) with $psr(L, \Gamma, C) < 1$, L can be said to be a useful lemma.

Dataset: Built From E Proofs

- **E's a saturation-based refutational ATP.**
- **Goal: Prove conjecture from premises.**
- **E has two sets of clauses:**
 - *Processed* clauses P (initially empty)
 - *Unprocessed* clauses U (Negated Conjecture and Premises)
- **Given Clause Loop:**
 - Select '*given clause*' g to add to P
 - Apply *inference rules* to g and all clauses in P
 - Process new clauses. Add non-trivial and non-redundant ones to U.
- **Proof search succeeds when empty clause is inferred.**
- **Proof consists of given clauses.**

Down and Dirty with the Dataset

- **3161 CNF problems from Mizar 40 dataset**
- **Proved by single E strategy**
- **For each clause L_i^P of proof P, solve both sub-problems.**
- **230528 clauses in total**

Lemma Stats

Of the 230528 clauses:

- **98472 are axioms and negated conjectures.**
- **87161 are anti-useful lemmas**
- **44895 are useful lemmas**
- **154 have $\text{psr}(L, \Gamma, C) = 1$**

Lemma Stats

- **Best lemma's psr: 0.0036 (275 times faster)**
- **Worst lemma: 77 times slower**
- **Number of lemmas under 0.1: 1509**

Lemma Classification

Why?

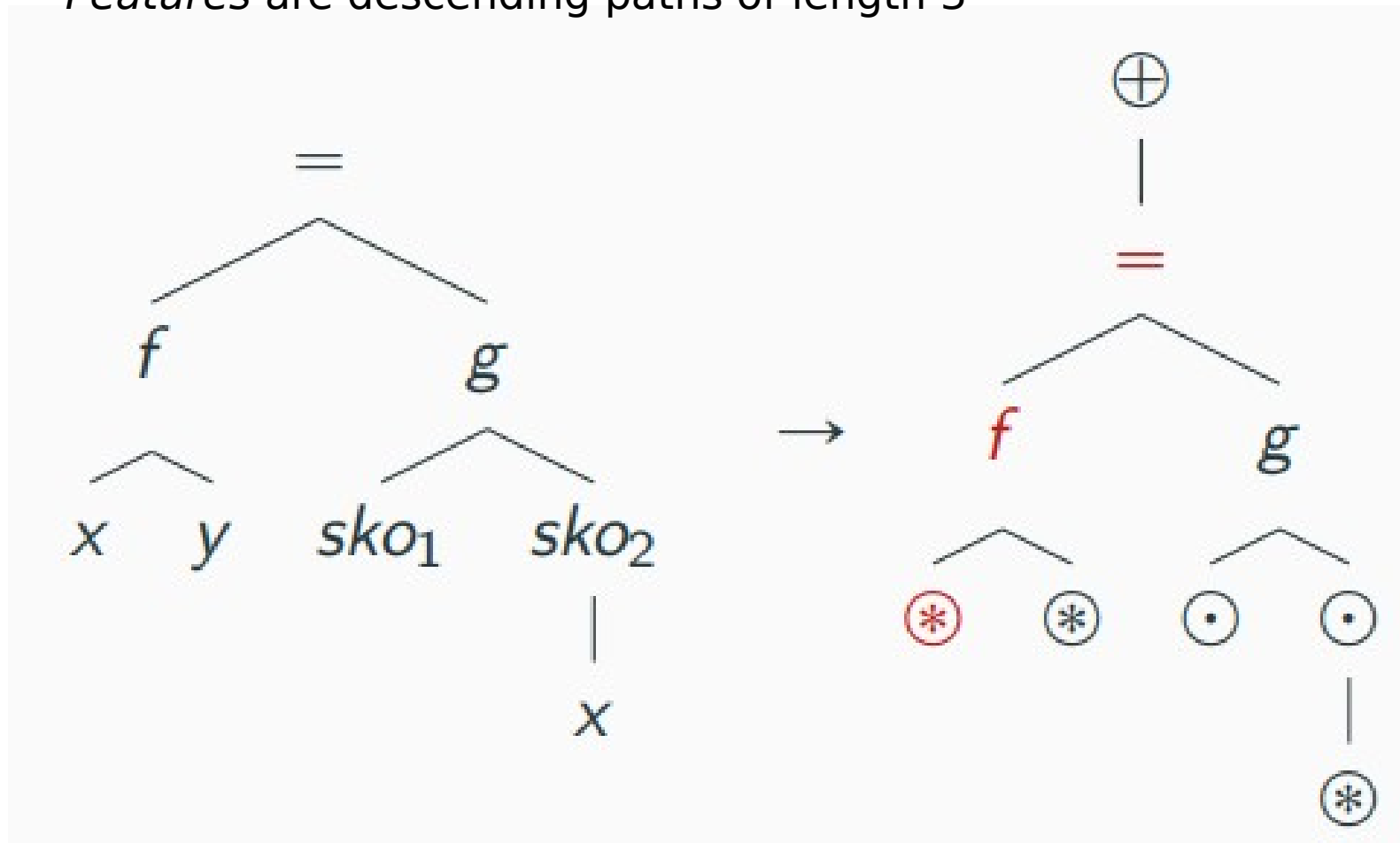
- **To gauge the difficulty of the dataset**
- **Clear yes/no results compared to regression**

Possible use-cases:

- **Proof compression for E inference guidance**
- **Analyze incomplete proof-search to look for lemmas**

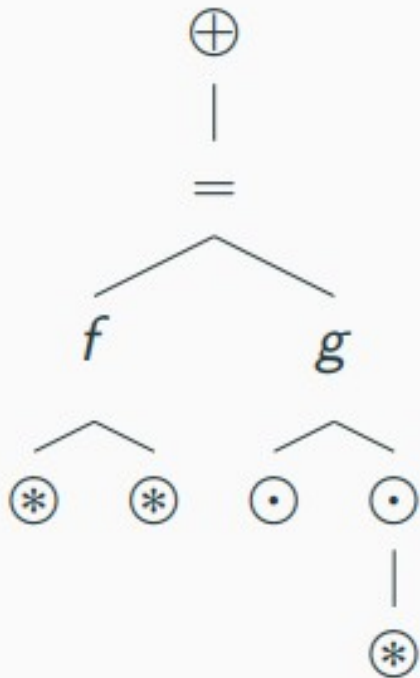
Clauses \longrightarrow Vectors

- Treat clause as tree. Abstract vars and skolem symbols
- *Features* are descending paths of length 3



Clauses \longrightarrow Vectors

Enumerate features ($\rightarrow \mathbb{R}^{|\text{Features}|}$ vector space)
Count features in a clause for its vector

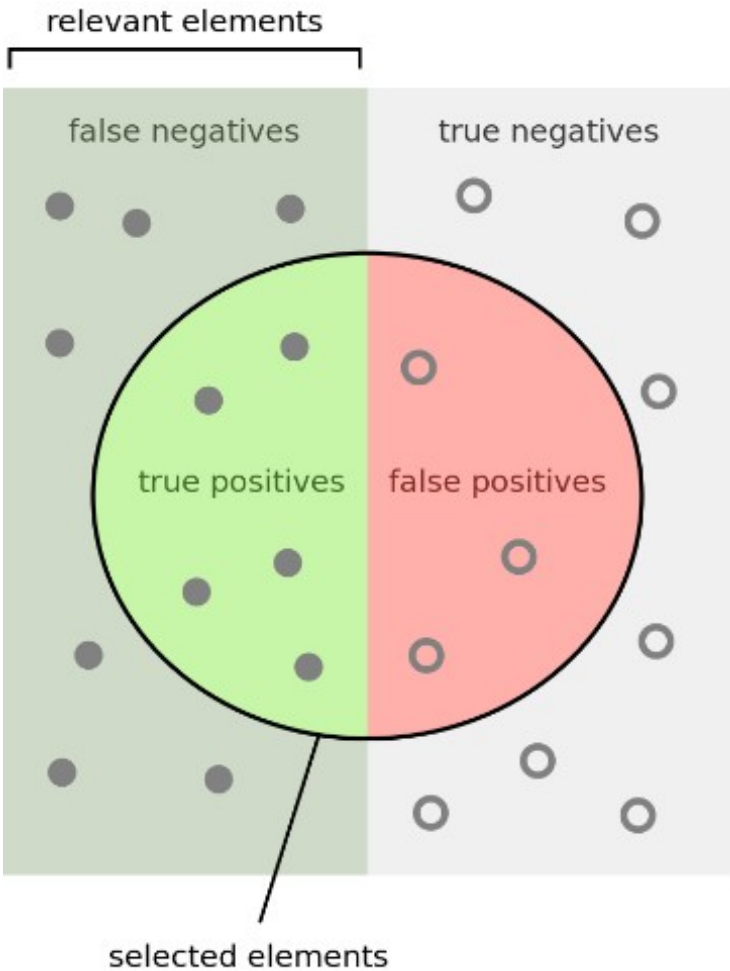


| # | feature | count |
|----------|-----------------------|----------|
| 1 | $(\oplus, =, a)$ | 0 |
| \vdots | \vdots | \vdots |
| 11 | $(\oplus, =, f)$ | 1 |
| 12 | $(\oplus, =, g)$ | 1 |
| 13 | $(=, f, \otimes)$ | 2 |
| 14 | $(=, g, \odot)$ | 2 |
| 15 | (g, \odot, \otimes) | 1 |
| \vdots | \vdots | \vdots |

ML Methods

- **Support Vector Machine Classifier (SVC) from scikit-learn**
- **XGBoost: gradient boosted random decision forest:**
 - SVC and XGBoost use |Clause ++ Conjecture| Enigma features.
- **Graph Attention Networks (GAT):**
 - Assign labels or numbers to nodes via the graph structure.
 - At each level, a node's features depend on its neighbors.
 - Drawback: graph adjacency matrix, large memory consumption
 - Question: Will the proof-graph structure help identify lemmas?

Results



How many selected items are relevant?

$$\text{Precision} = \frac{\text{true positives}}{\text{true positives} + \text{false positives}}$$

How many relevant items are selected?

$$\text{Recall} = \frac{\text{true positives}}{\text{true positives} + \text{false negatives}}$$

F score

$$2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$$



Results

| | F-score | Precision | Recall | Accuracy |
|---------|---------|-----------|--------|----------|
| SVC | 0.53 | 0.45 | 0.64 | 0.74 |
| GAT | 0.55 | 0.45 | 0.72 | 0.55 |
| XGBoost | 0.68 | 0.65 | 0.72 | 0.77 |

Results are on a 10% test set.

Precision and Recall are with respect to useful lemmas.

Conclusions

-  • **GAT appears not to scale, and the proof-graph is not effectively utilized.**
-  • **XGBoost is cheap to train and sufficiently effective as to be used in further experiments with E.**

Todo:

- **Learn more semantic features**
- **Work on generating lemmas**

