

Make E Smart Again

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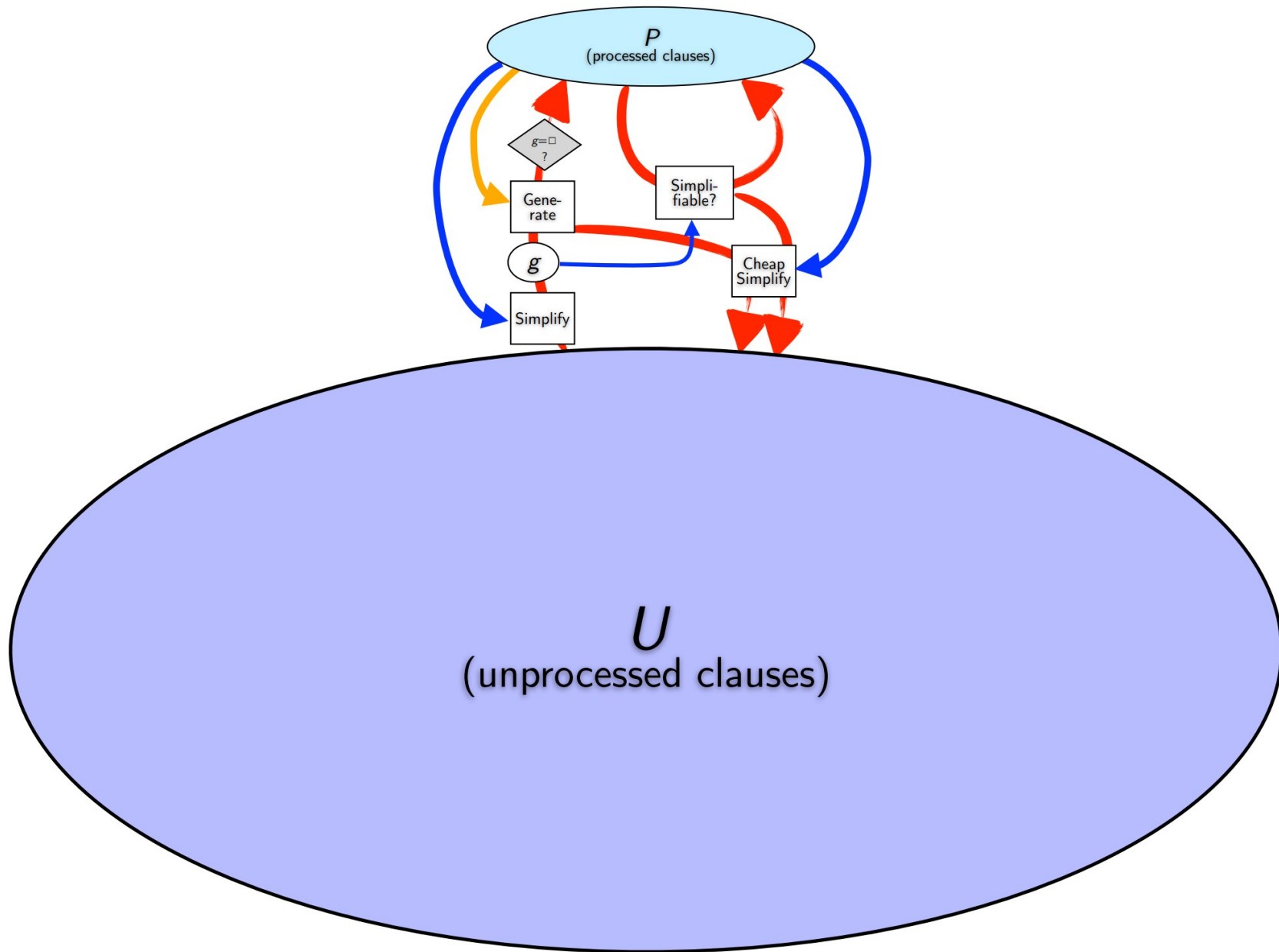
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E Prover (a Saturation-based ATP)

- **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 some of the given clauses.**

Given Clause Loop in E



E Strategies

A strategy guides E's proof search.

The main components:

- **Clause Evaluation Functions**
- **Term ordering**
- **Literal selection**

E Strategies

- *Clause Evaluation Functions* consist of:
 - *Priority functions*: partition clauses into priority queues.
 - e.g., *ConstPrio*, *PreferUnit*
 - **Weight functions**: order clauses in queues based on a score.
 - e.g.: **Clauseweight**, **FIFOWeight**
- Weighted by frequency of use, for example, :

**-H'(5*Clauseweight(ConstPrio,1,1,1),
1*FIFOWeight(ConstPrio))'**

Strategy E1

```
--definitional-cnf=24 --split-aggressive --simul-paramod  
--forward-context-sr --destructive-er-aggressive --  
destructive-er --prefer-initial-clauses -tKBO -  
winvfreqrank -c1 -Ginvfreq -F1 --delete-bad-  
limit=150000000 -WSelectMaxLComplexAvoidPosPred -  
H(1*ConjectureTermPrefixWeight(DeferSOS,1,3,0.1,5,0,0  
.1,1,4),1*ConjectureTermPrefixWeight(DeferSOS,1,3,0.5,  
100,0,0.2,0.2,4),1*Refinedweight(PreferWatchlist,4,300,  
4,4,0.7),1*RelevanceLevelWeight2(PreferProcessed,0,1,  
2,1,1,1,200,200,2.5,9999.9,9999.9),1*StaggeredWeight(  
DeferSOS,1),1*SymbolTypeweight(DeferSOS,18,7,-  
2,5,9999.9,2,1.5),2*Clauseweight(PreferWatchlist,20,99  
99,4),2*ConjectureSymbolWeight(DeferSOS,9999,20,50,-  
1,50,3,3,0.5),2*StaggeredWeight(DeferSOS,2))
```

Strategy E2

```
--definitional-cnf=24 --split-aggressive --split-  
reuse-defs --simul-paramod --forward-context-sr  
--destructive-er-aggressive --destructive-er --  
prefer-initial-clauses -tKBO -winvfreqrank -c1 -  
Ginvfreq -F1 --delete-bad-limit=150000000 -  
WSelectMaxLComplexAvoidPosPred -  
H(3*ConjectureRelativeSymbolWeight(PreferUnit  
GroundGoals,0.1,100,100,50,100,0.3,1.5,1.5),4*F  
IFOWeight(PreferNonGoals),5*RelevanceLevelWe  
ight2(ConstPrio,1,0,2,1,50,-2,-2,100,0.2,3,4))
```

E Strategies

- *Term orderings:*
 - Determine rewrite order
 - Contribute to completeness of proof search
 - Prevent cycles

E Strategies

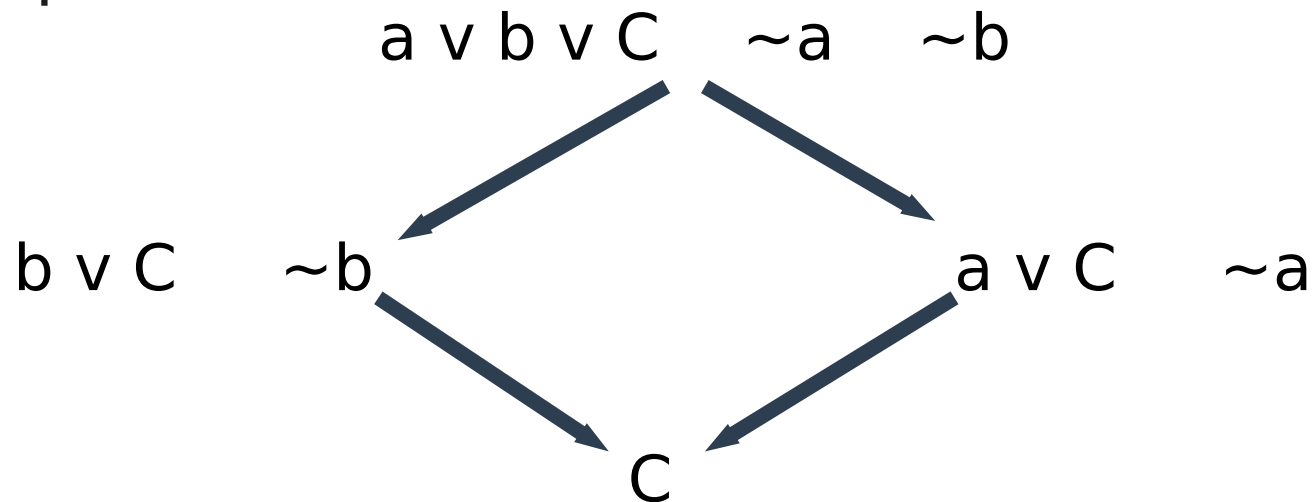
- Term orderings:
 - Determine rewrite order
 - Contribute to completeness of proof search
 - Prevent cycles
- For example, given $x+0=0$,
 - $x+0 \rightarrow x$ is valid
 - $x \rightarrow x+0$ is invalid

E Strategies

- Term orderings:
 - Determine rewrite order
 - Contribute to completeness of proof search
 - Prevent cycles
- For example, given $x+0=0$,
 - $x+0 \rightarrow x$ is valid
 - $x \rightarrow x+0$ is invalid
- Our strategies use KBO: Kunth-Bendix ordering

E Strategies

- Literal selection limits resolution.
 - Limits redundancy
 - Contributes to completeness.
- For example,



ENIGMA

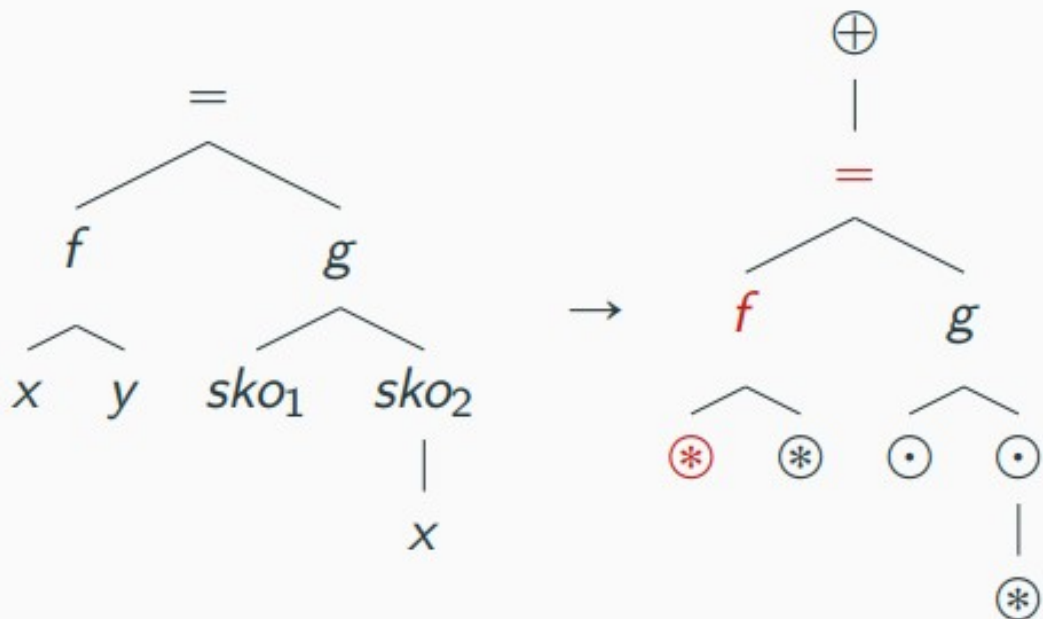
- **Statistical Learning**
 - XGBoost
- **Learns from given-clauses**
- ***Positive and Negative***
- **Maps clauses to vectors**
- **Weight function**
- **Ranks all clauses**
- **Input:**
 - Positive examples + conjecture features
 - Negative examples + conjecture features
- **Output:**
 - Fast model to predict whether (clause, conjecture) pairs are *positive* or *negative*.

Clauses \longrightarrow Vectors

- Treat clauses as trees. Abstract vars and skolem symbols

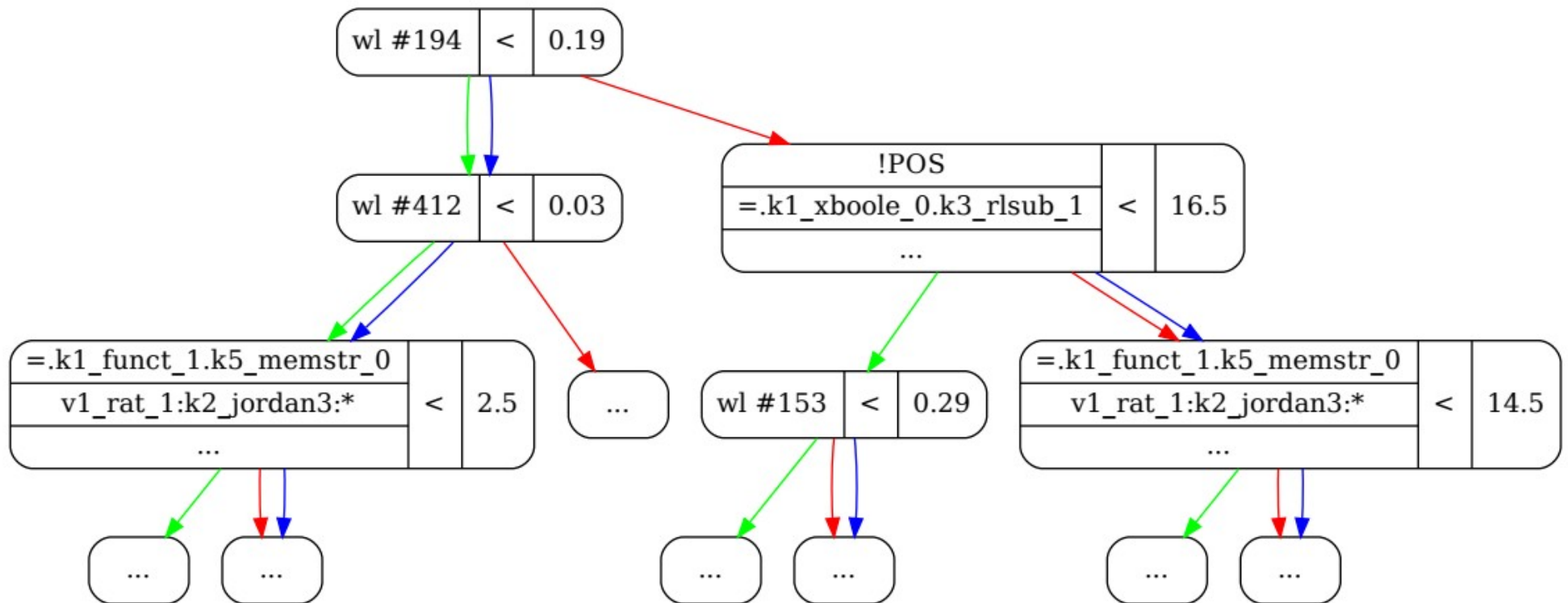
- Enumerate features:
Count features in a clause for its vector

For example: $f(x, y) = g(\text{sko}_1, \text{sko}_2(x))$



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

XGBoost Example Tree



Dataset

- Mizar Mathematical Library (MML) contains 1148 articles and 57880 theorems:
 - including *Bolzano-Weierstrass* and *Gödel's completeness theorem*
- An interactive theorem proving system
- Premises are already selected.

Previous ENIGMA results:

On all 57880 Mizar problems:

- *E1*: 14526
- *E2*: 12778
- *ENIGMA*: 25562 (+76%)

Research Question

- **Can ENIGMA learn to guide E without its strategies?**

Method:

- 1) Make E stupid.
- 2) Try to learn!

Making E Stupid: E0

1) Replace KBO with structural identity relation

- (Which disables term rewriting!)

2) Disable literal selection

3) Use only the basic strategy:

```
--definitional-cnf=24 --prefer-initial-clauses  
-tIDEN -restrict-literal-comparisons  
-H'(5*Clauseweight(ConstPrio,1,1,1),  
1*FIFOWeight(ConstPrio))'
```

ENIGMA Training

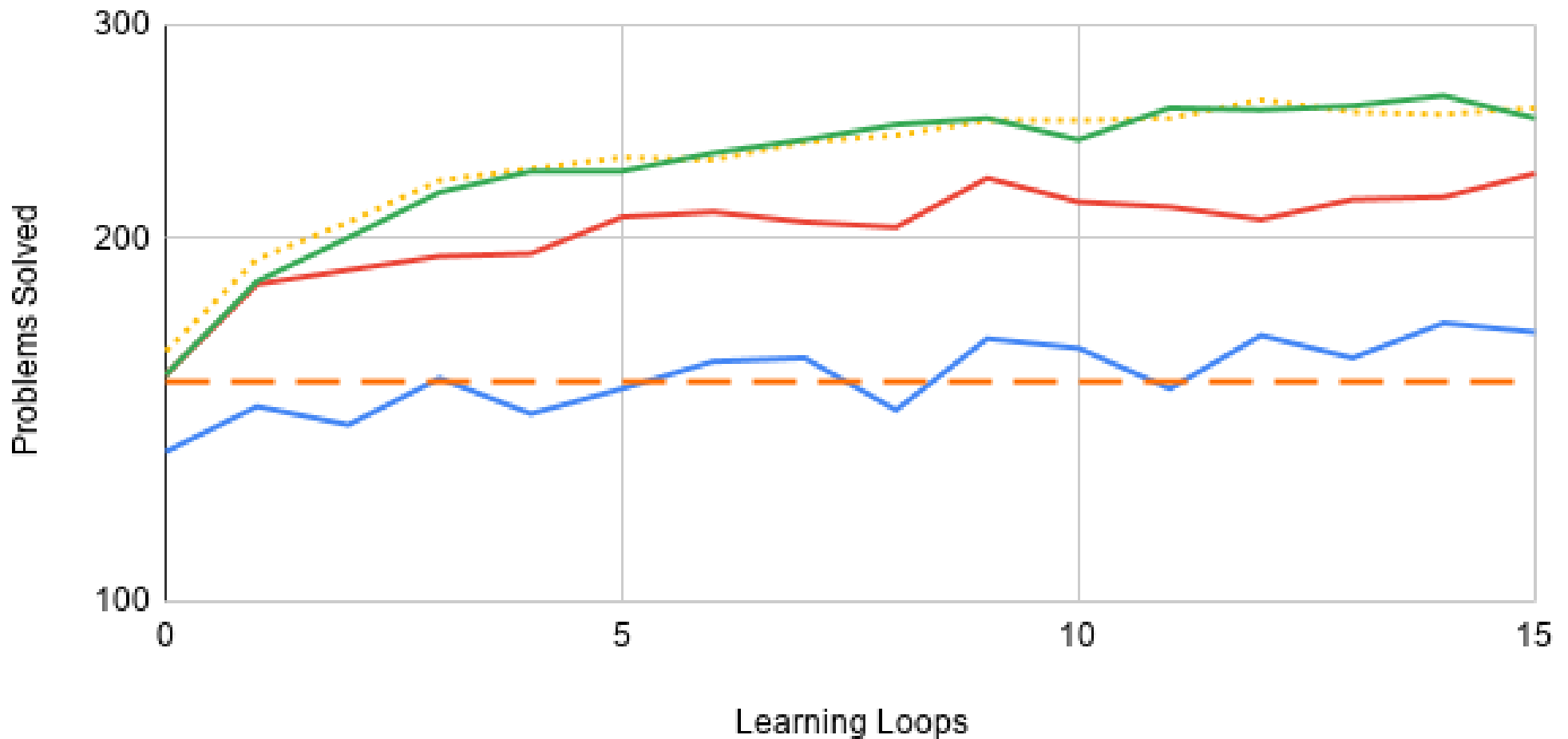
- 1) Run E0**
- 2) Train a model.**
- 3) Run E0 with the model (loop 0).**
- 4) Repeat.**

Hyper-parameters:

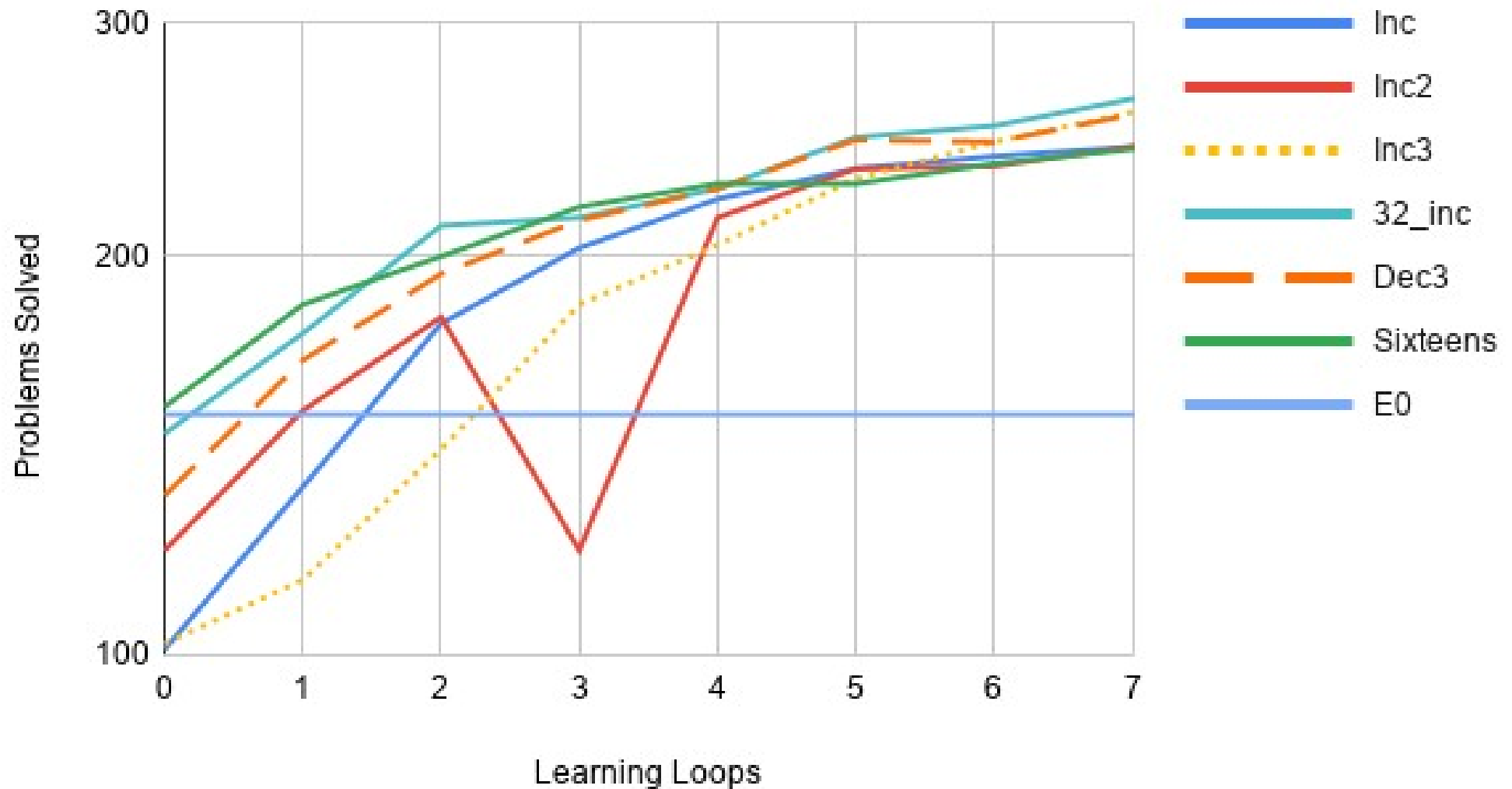
- Number of loops**
- Number of trees per loop**
- Depth of trees**

Small Data (2000) - Constant Parameters

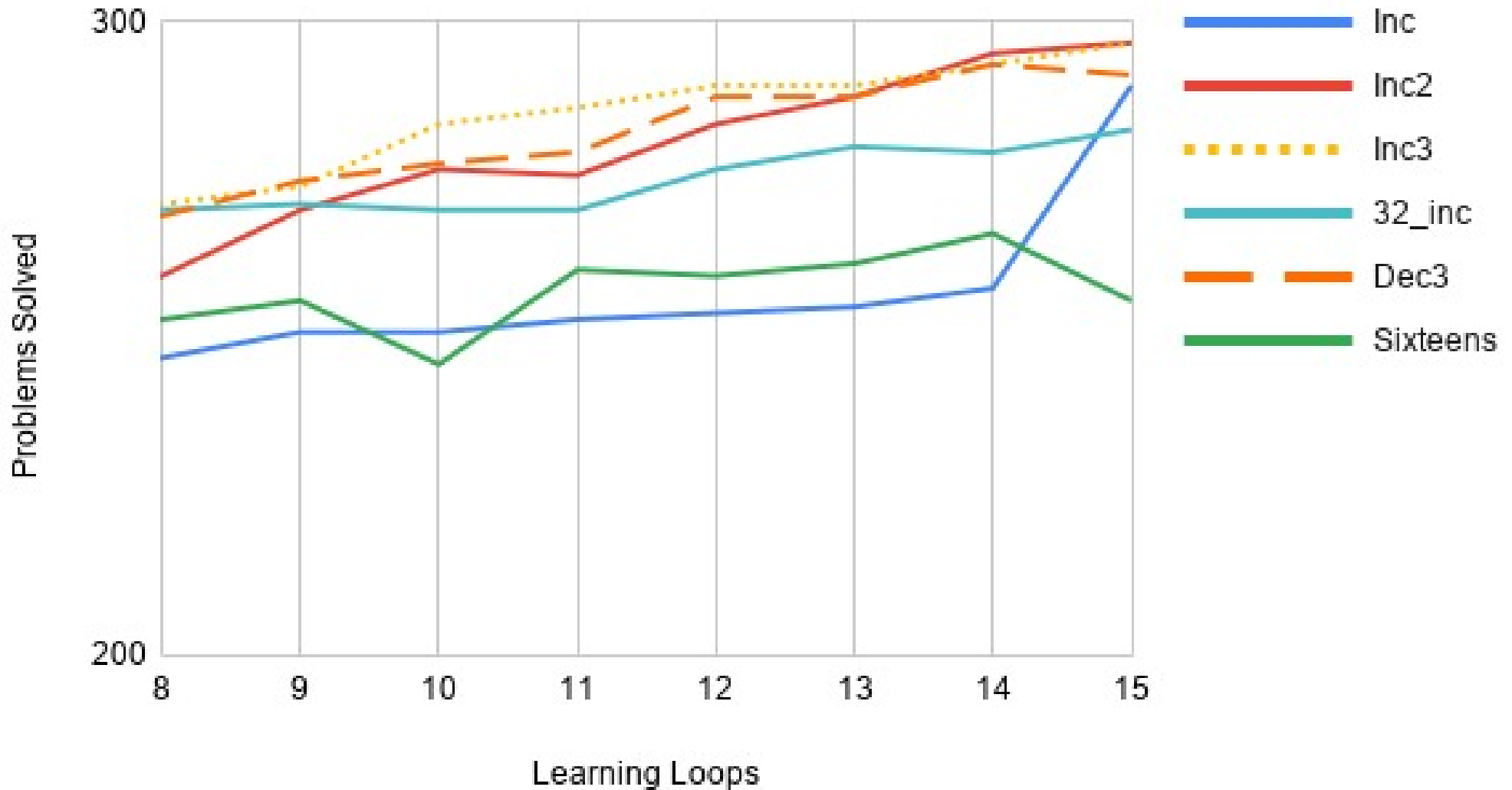
Fives Nines Thirteens Sixteens E0



Small Data (2000) - Adaptive Parameters

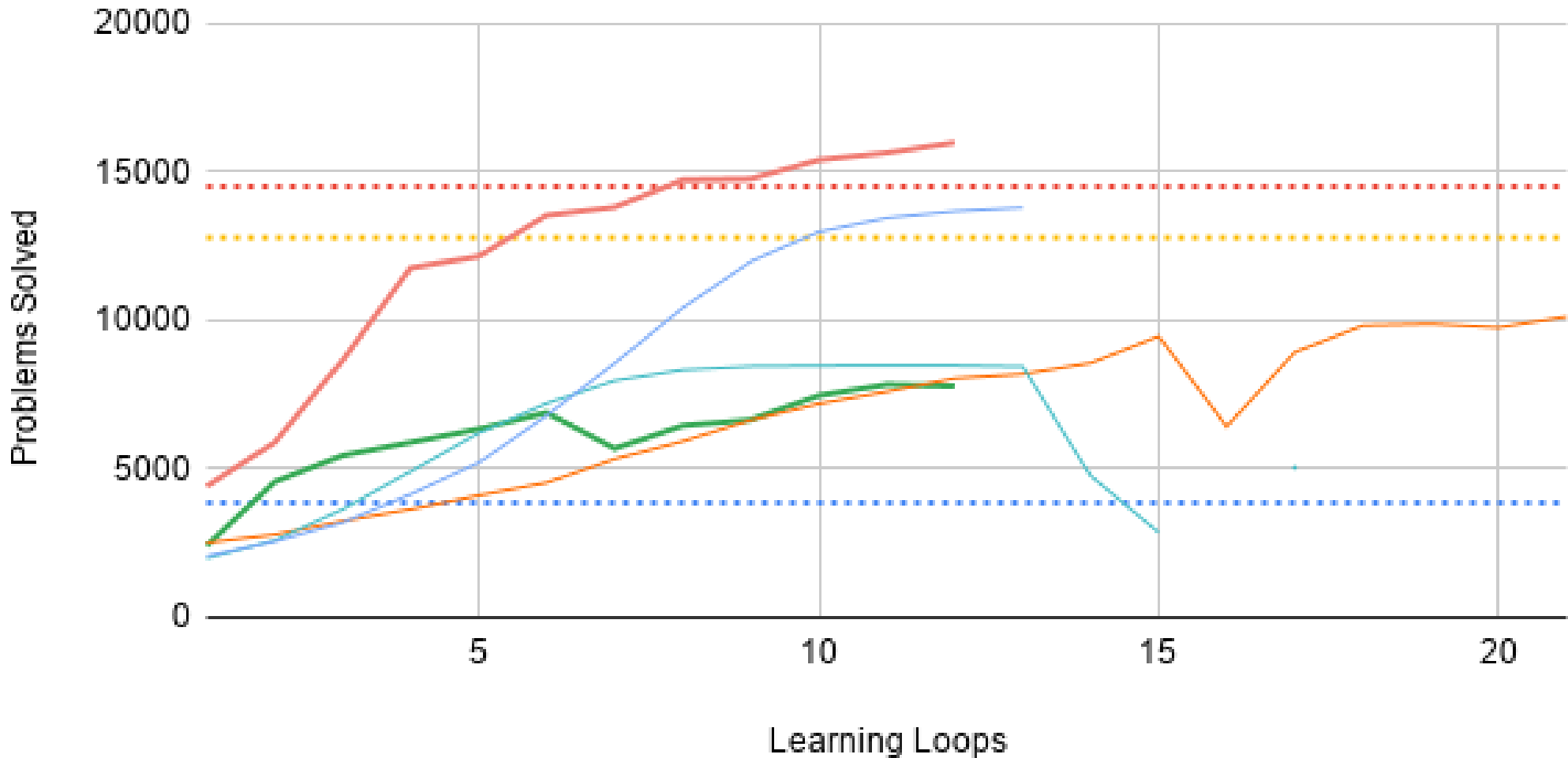


Small Data (2000) - Adaptive Parameters



Big Data (57880)

E0 E1 E2 Exp. 1 Exp. 2 Exp. 3 Exp. 4 Exp. 5



Conclusion

- Can ENIGMA learn to guide E without its strategies?
 - Yes!
 - 256% increase w/ additional training data.
 - 156% increase trained on E0 data alone.
- Term ordering and literal selection are still helpful.
- Can the gap be bridged?
 - Perhaps by ENIGMA-NG..
- Will relaxing term ordering help combine strategies?

References

- **Stephan Schulz' slides on E with good graphics:**
<http://aitp-conference.org/2016/slides/StSGuidance.pdf>