Improving Term Extraction with Acyclic Constraints

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Overview

- + Term Extraction
- + Extraction with ILP and its challenge
- + Our contribution: Acyclic constraints

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<u>Inputs:</u> e-graph; root e-class(es); cost model <u>Output:</u> term(s) w/ the minimum cost

























Greedy works in most cases, but may fail by yielding sub-optimal solutions



Yisu Remy Wang, Shana Hutchison, Jonathan Leang, Bill Howe, & Dan Suciu. (2020). SPORES: Sum-Product Optimization via Relational Equality Saturation for Large Scale Linear Algebra. Yichen Yang, Phitchaya Mangpo Phothilimtha, Yisu Remy Wang, Max Willsey, Sudip Roy, & Jacques Pienaar. (2021). Equality Saturation for Tensor Graph Superoptimization.







Extracted by Greedy (29)



Optimal (25)

Alternative: Integer linear programming (ILP)

For each e-node *n*, create a **binary (0/1) variable** W_n (call them node variables)

Root Constraint: $\sum w_n \ge 1$ for all *n* in the root e-class

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Avoiding Cycles: Topological sorting (ILP-Topo)

For each e-class C, create an integral value t_C bounded by a sufficiently large value σ (e.g. 2x number of the e-classes)

"If we pick an e-node *n*, then the topological order of its e-class must be greater than those of all its children."

Too expensive!

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Acyclic Constraints



X + Y



$X + Y + Z + W \le 3$

 $\neg X \lor \neg Y \lor \neg Z \lor \neg W$

Background: Weighted (Partial) MaxSAT

Weighted: clauses carry a positive weight.



SAT soft clauses.



maximize the sum of weights of

For each e-node n, create a **boolean variable** w_n (call them node variables)

Hard Clauses

Root Constraints Children Constraints Acyclic Constraints

Soft Clauses $\neg w_n$

Soft constraints are simply $\neg w_n$ for each e-node *n* with weights cost(*n*).

Soft Clauses

 $\neg W_n$

Hard Clauses

Root Constraint: $\bigvee W_{n_i}$

Acyclic constraints (naiv

Children Constraints:
$$w_n \rightarrow \bigvee_{n' \in C_i} w_{n'}$$

re):
$$\bigvee \neg w_n$$
 (for all cycles ϕ)
 $n \in \phi$

Reducing # of Acyclic Constraints

Acyclic constraints (naive): $\bigvee_{n \in \phi} \neg w_n$ (for all cycles ϕ)

The naïve encoding could yield exponentially many constraints for a single cycle of e-classes



Reducing # of Acyclic Constraints

Instead of encoding on cycles of e-nodes, we could instead work with cycles of e-classes





Tseitin $((\neg w_A \land \neg w_B) \lor (\neg w_C \land \neg w_D) \lor (\neg w_E \land \neg w_F))$

$$\Leftrightarrow$$
$$x_{AB} \leftrightarrow (\neg w_A \land \neg w_B)$$
$$x_{CD} \leftrightarrow (\neg w_C \land \neg w_D)$$
$$x_{EF} \leftrightarrow (\neg w_E \land \neg w_F)$$
$$x_{AB} \lor x_{CD} \lor x_{EF}$$



ILP Encoding

Replacing the topological ordering constraints with acyclic constraints.

 $x_{C_i} \leftarrow$

If direction: (1 -

Only-if direction: x_{C_i} +

Following Tseitin Transformation:

Call this encoding as **ILP-ACyc**

$$\rightarrow \bigwedge \neg w_j$$

$$+ x_{C_i} + (1 - w_j) \ge 1$$

$$+ \sum w_j \ge 1$$

$$x_{C_i} \ge 1$$

1

WPMAXSAT and ILP-ACyc

Remaining Issue: # of cycles of e-classes?



O(n) constraints per e-class cycle



WPMAXSAT and ILP-ACyc

Remaining Issue: # of cycles of e-classes?



O(n) constraints per e-class cycle

Worst case... $O(2^{|C|})$

Experiments

Evaluation setup

Workload:

Extracting optimal terms from saturated e-graphs from Glenside¹ Tensor programs are obtained from ResNet-18/50, MobileNet, ResMLP and EfficientNet.

Rewrite Rules:

Im2Col: image-to-column transformations Im2Col + SIMPL: Im2Col plus a set of simplification rewrites, including

- Operator collapsing (transpose, reshape, access, etc.)
- Operator reordering

Configurations:

5-second timeout for equality saturation

5-minute timeout for term extraction (including time of constructing constraints)

1: Gus Henry Smith, Andrew Liu, Steven Lyubomirsky, Scott Davidson, Joseph McMahan, Michael Taylor, Luis Ceze, & Zachary Tatlock (2021). Pure tensor program rewriting via access patterns (representation pearl). In Proceedings of the 5th ACM SIGPLAN International Symposium on Machine Programming. ACM.

Results

E-graph statistics

	MobileNet	ResMLP	ResNet-18	EfficientNet
IM2COL	17266	15819	14754	21016
IM2COL + SIMPL	17320	4247	4466	10978

Table 1. Class cycle count after equality saturation

Good News!







Constraint building + term extraction time





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TY!

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Discussion

LP Relaxation of ILP-Topo

Relaxation is not trivial:

"Weight vanishing"
Recall Children constraints:
$$-w_n + \sum_{n' \in C_i} w_{n'} \ge 0$$

 w_n could be distributed over e-nodes in its children e-classes.

