Declarative Machine Learning for Energy Efficient Compiler Optimizations

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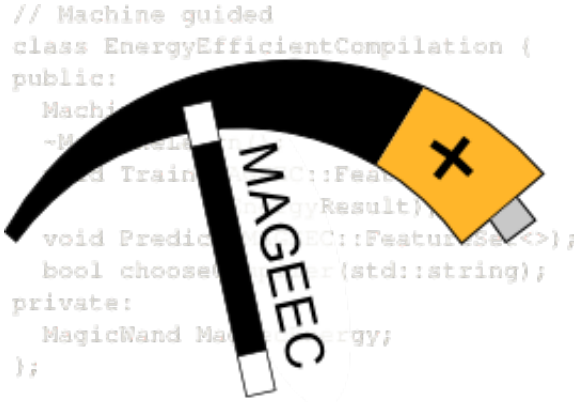
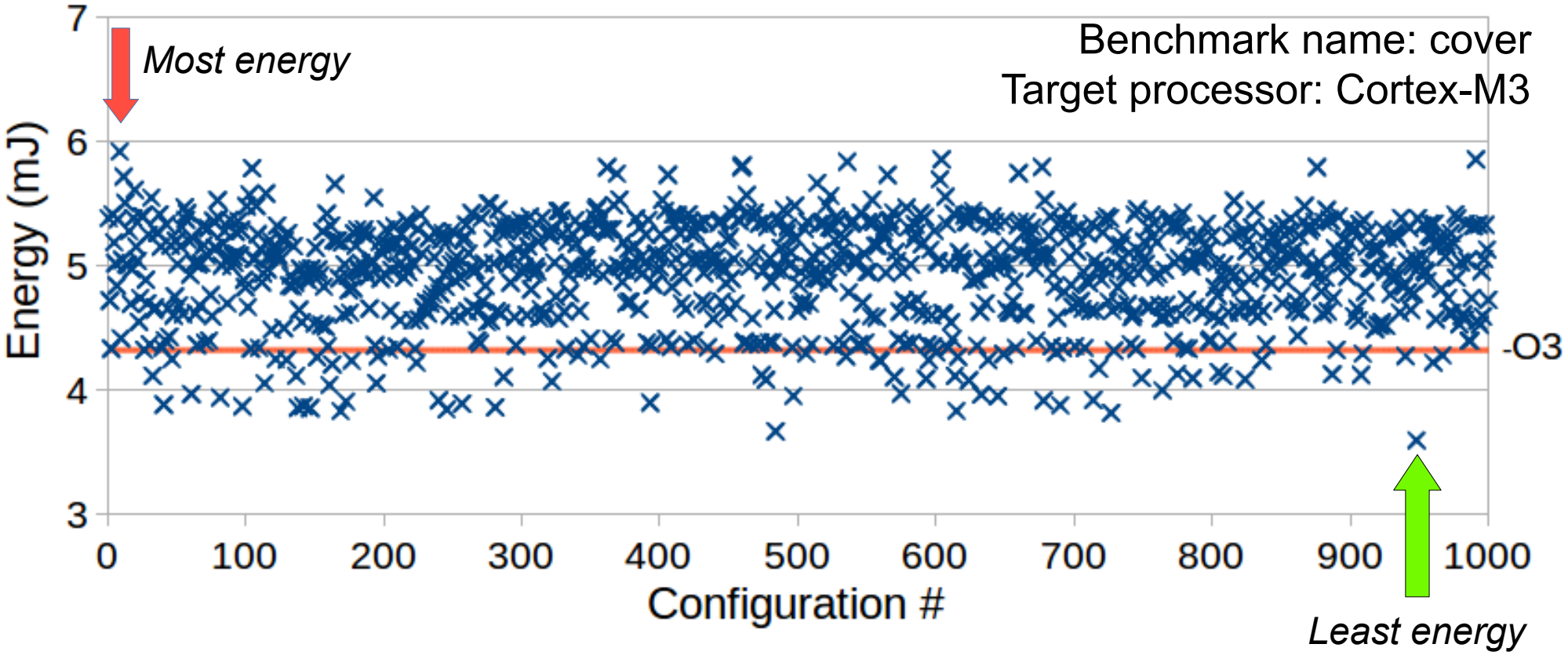


1000 Random Configurations



✗ Exhaustive search infeasible

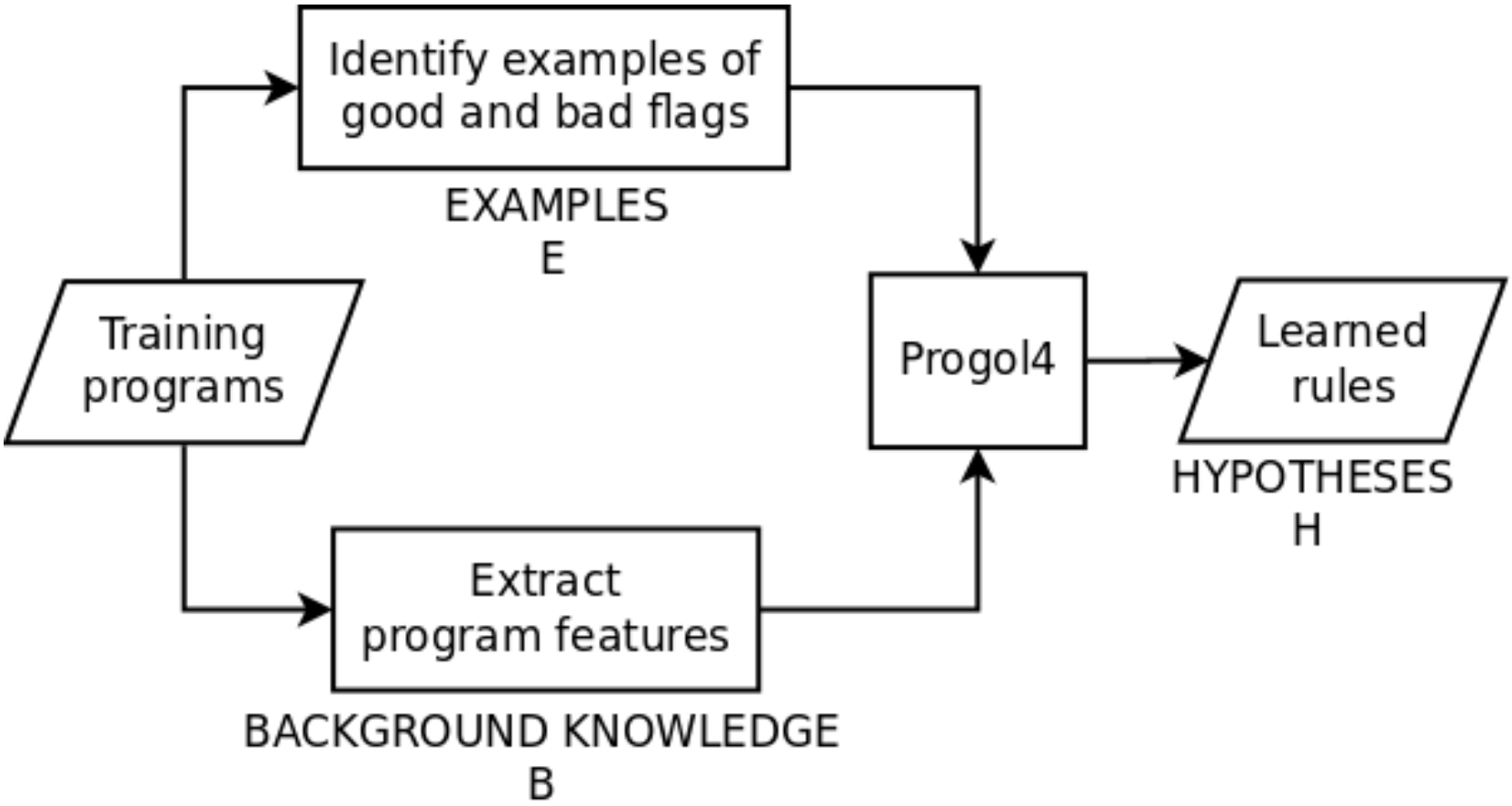
✗ Random sampling (iterative compilation) slow

✔ **Predictive approaches**

Inductive Logic Programming

- **Declarative inductive learning method**
- Requires:
  - Factual examples *E* represented as components together with their relationships, and
  - Background knowledge *B* describing these relations.
- Finds a single (or multiple) hypothesis *H*
  - expressed in terms of the relations given in *B*
  - such that every positive and (ideally)
  - no negative example in *E* is covered by *H*.

ILP for MAGEEC



Specific examples → General Rules

Identifying Good/Bad Flags

1000 random configurations for each benchmark

Good flag = appears frequently in top configurations

Bad flag = not a good flag ☺

Examples *E* for Progol:

goodFlag(program1, -finline-functions).	Positive Example
:- badFlag(program1, -finline-functions).	Negative Example

Feature Extraction

Prolog queries regarding the program features + utility functions:

Ft1 - Number of basic blocks

featlstn.P : ft(ft1,N) :- findall(B,bb_p(B),L), count_lst(L,N).

Ft5 - Number of basic blocks with a single predecessor

featlstn.P :

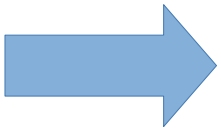
```
edge_dest_pr2(B,N) :- bb_p(B), findall(E,edge_dest(E,B),L),
count_lst(L,N).
edge_dest_pr2_sel1(B) :- edge_dest_pr2(B,N), N = 1.
ft(ft5,N) :- findall(B,edge_dest_pr2_sel1(B),L), count_lst(L,N).
```

Feature Extraction

- Ft15 - Number of basic blocks with number of instructions greater than 500
  - featlstn.P :
    - bb_stmt_in(B,ST) :- bb_stmt_f(B,ST).
    - bb_stmt_in(B,ST) :- bb_stmt_n(B,_,ST).
    - bb_stmt_in_pr1(B,N) :- bb_p(B), findall(ST,bb_stmt_in(B,ST),L), count_lst(L,N).
    - bb_stmt_in_pr1_sel3(B) :- bb_stmt_in_pr1(B,N), N > 500.
    - ft(ft15,N) :- findall(B,bb_stmt_in_pr1_sel3(B),L), count_lst(L,N).

Background Knowledge

Feature 1 = 0.5
Feature 2 = 0.7
Feature 3 = 0.32
...



ft(ft1, program1, 0.5).
ft(ft2, program1, 0.7).
ft(ft3, program1, 0.32).
...

Background relations:

quartile(P,Ft,1) :- ft(Ft,P,N), qt1(Ft,Q1), N=<Q1.
quartile(P,Ft,2) :- ft(Ft,P,N), qt1(Ft,Q1), qt2(Ft,Q2), N>Q1, N=<Q2.
quartile(P,Ft,3) :- ft(Ft,P,N), qt2(Ft,Q2), qt3(Ft,Q3), N>Q2, N=<Q3.
quartile(P,Ft,4) :- ft(Ft,P,N), qt3(Ft,Q3), N>Q3.

Background Knowledge

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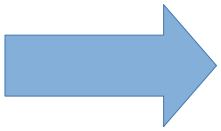

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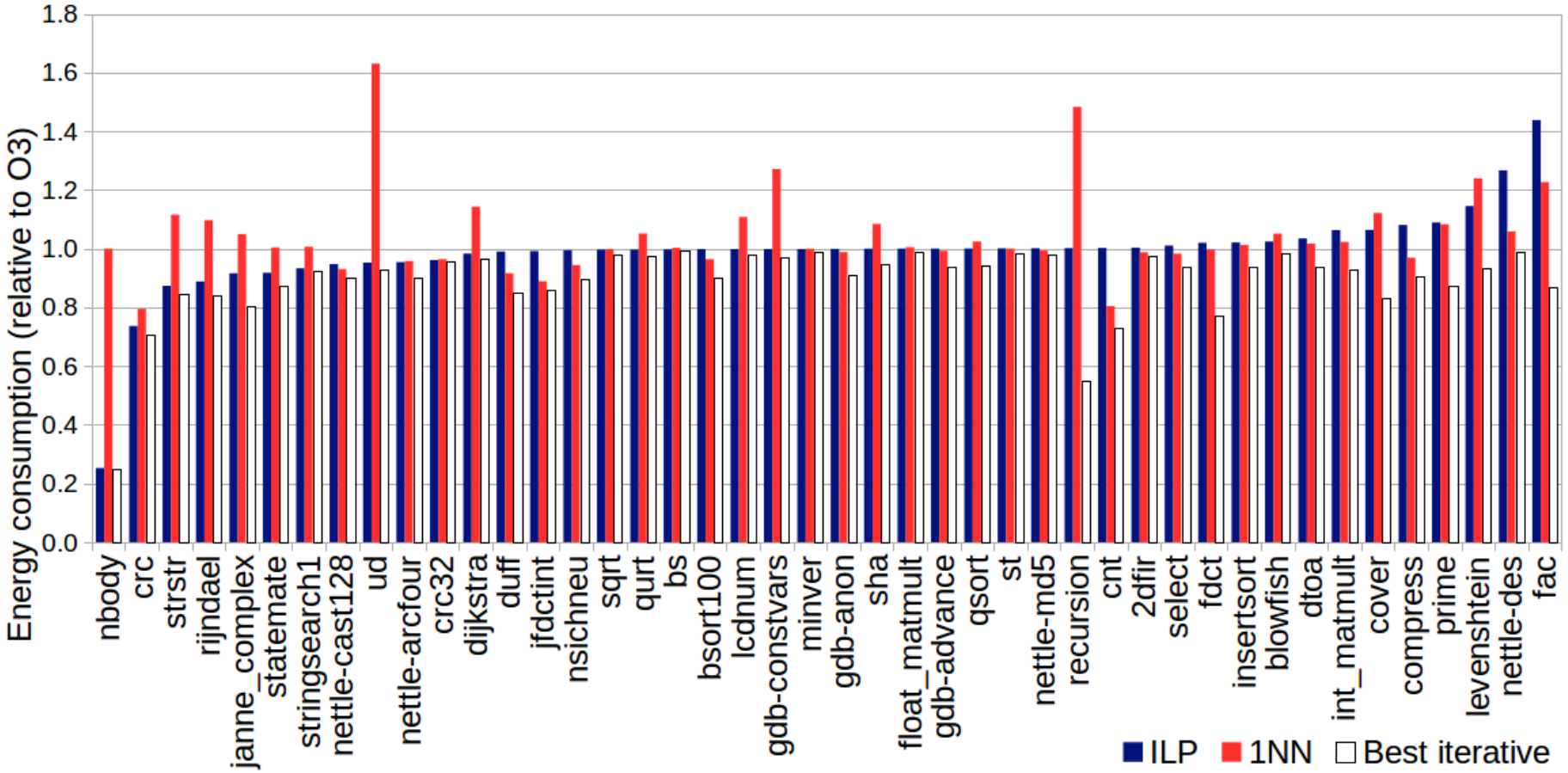
quartile(P,Ft,4) :- ft(Ft,P,N), qt3(Ft,Q3), N>Q3.

Learning Results

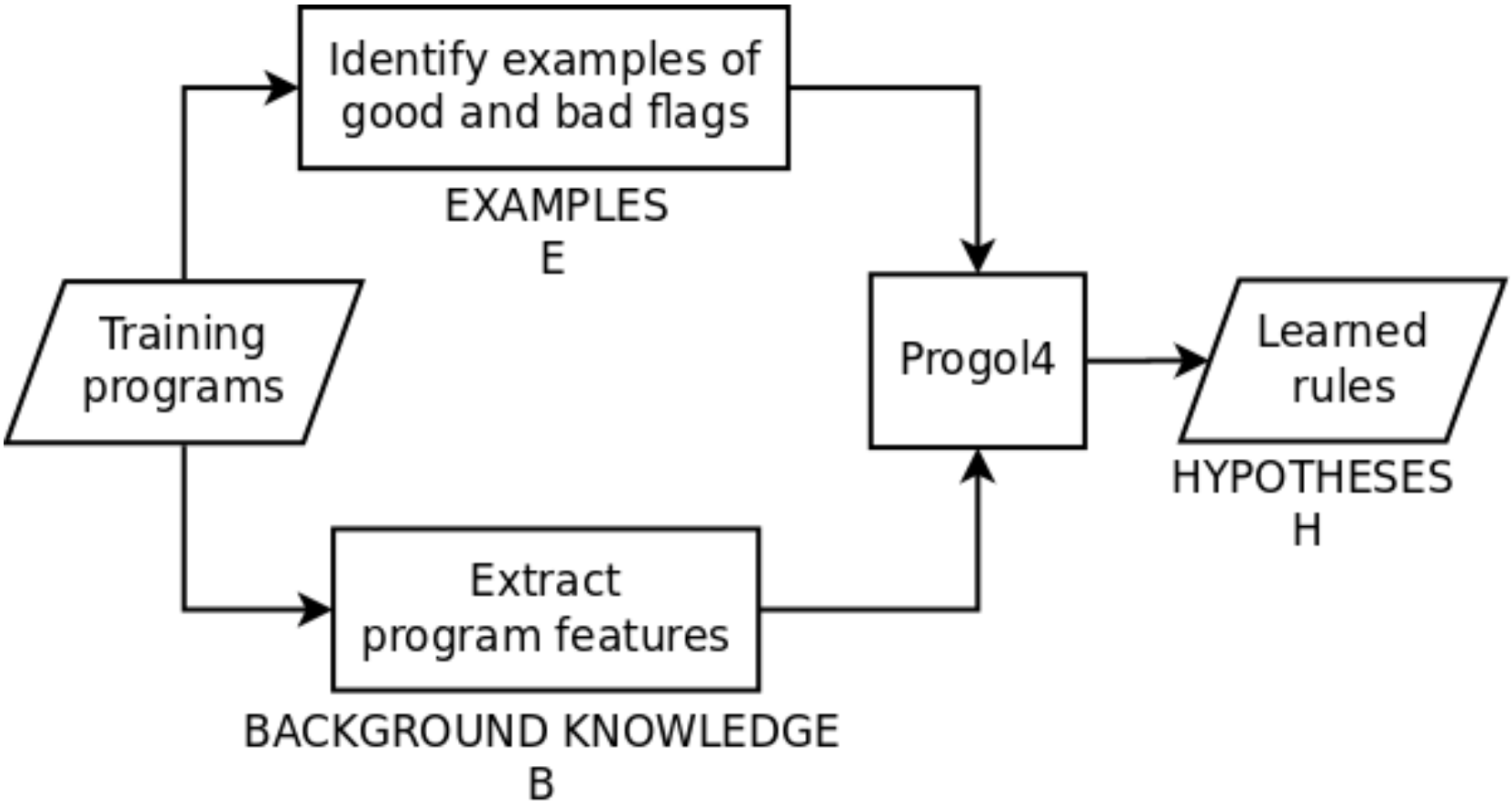
goodFlag(A,-finline-small-functions).

badFlag(A,-fsection-anchors) :- quartile(A,ft22,3).

Preliminary Results: Leave-One-Out Cross Validation

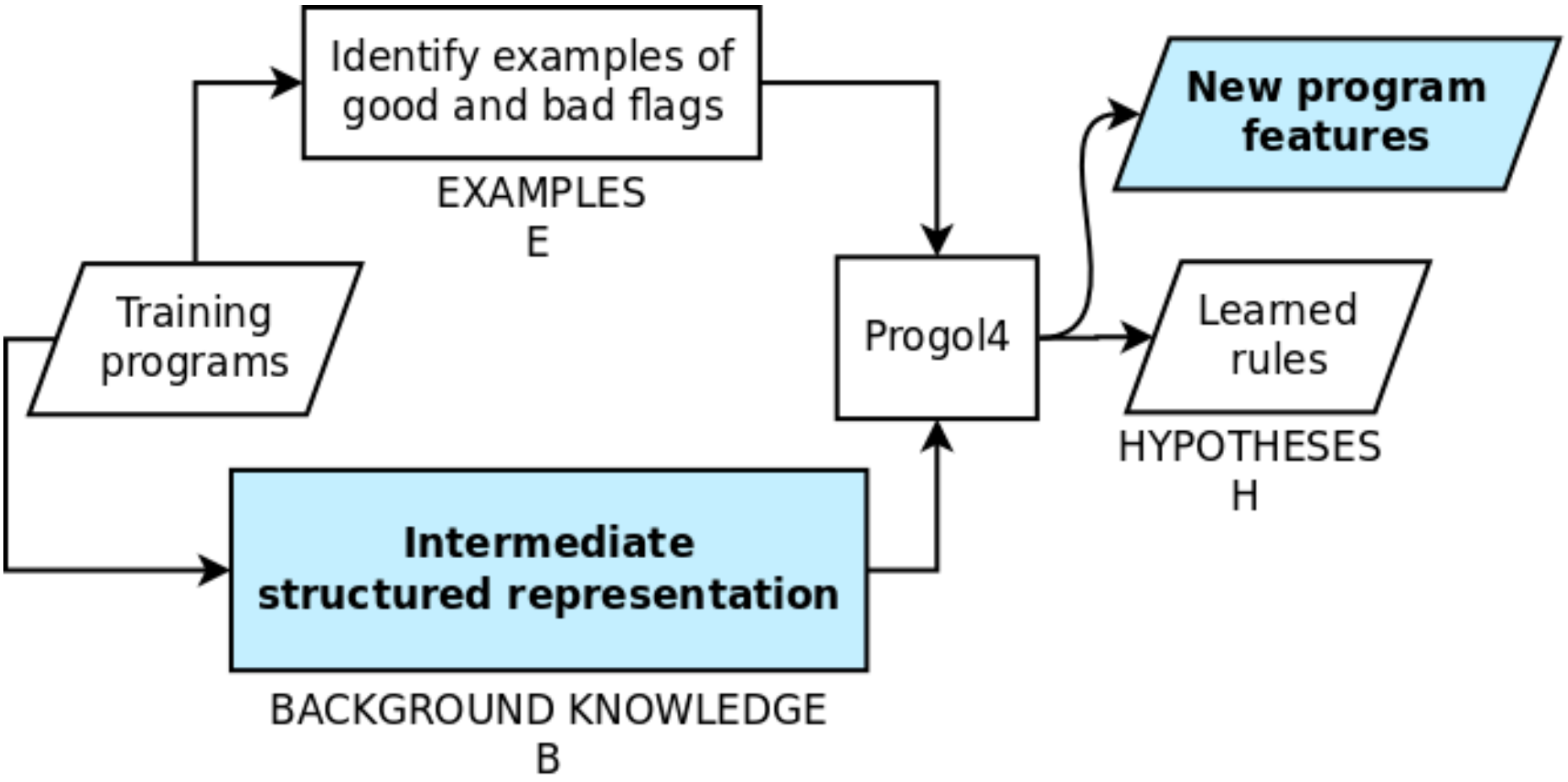


ILP for MAGEEC



Specific examples → General Rules

Future Work



Specific examples → General Rules

Questions?

Craig Blackmore, Kerstin Eder and Oliver Ray
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