## Polyhedral Binary Decision Diagrams for Representing Non-Convex Polyhedra

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## Polyhedral Model

## Simple Program


$\{S(i, j) \mid 0<i, j \wedge i+j<6\}$
Statement Domain Visualization

## Polyhedral Compilation

Use the polyhedral model for:

* Program Analysis
* Check the legality of a program transform
*E.g. Loop interchange
*Eventually need to solve a system of linear/affine inequalities
* Statement Scheduling
*Form a "better" schedule according to some objective
*E.g. parallelism, data locality, memory access
* Eventually need to solve an Integer Linear Program (IntLP)


## Convexity, A Crucial Requirement

Statement domain must be convex for compact polyhedral representation

* Does not hold for programs with conditional statements



## Union-of-Convex-Polyhedra

* Non-convex vector sets are represented as union of convex polyhedra

```
for (int i = 1; i <= 6; ++i)
    for (int j = 1; j <= 5; ++j)
        if (i != 3 || j!= 3)
            Stmt(i,j);
```





## Motivating Example

* Conditionals introduce non-affine constraints (eg non-equality), which leads to splitting of iteration domain

```
for (int i = 0; i < n; i+=1) {
    for (int j = 0; j< n; j+=1) {
        for (int k = 0; k < n; k+=1) {
        Stmt(i, j, k);
        }
    }
}
```

for (int $\mathrm{i}=0 ; \mathrm{i}<\mathrm{n}$; $\mathrm{i}+=1$ ) \{
for (int $j=0 ; j<n ; j+=1$ ) \{
for (int $k=0 ; k<n ; k+=1$ ) \{
if ( $\mathrm{i}=\mathrm{p} 0$ )
continue;
Stmt(i, j, k);
\}
\}
for (int $i=0 ; i<n ; i+=1$ ) \{ for (int $j=0 ; j<n ; j+=1$ ) \{ for (int $k=0 ; k<n ; k+=1$ ) \{ if (i == p0) continue; if ( $\mathrm{j}==\mathrm{p} 1$ ) continue; Stmt(i, j, k);
\}

for (int $\mathrm{i}=0$; $\mathrm{i}<\mathrm{n}$; $\mathrm{i}+=1$ ) \{ for (int $\mathrm{j}=0 ; \mathrm{j}<\mathrm{n} ; \mathrm{j}+=1$ ) \{ for (int $k=0 ; k<n ; k+=1$ ) \{
if ( $\mathrm{i}=\mathrm{p} 0$ )
continue;
if ( $\mathrm{j}=\mathrm{p} 1$ ) continue;
if (k == p2) continue; Stmt(i, j, k)
\}
\}


## Polly

*The previous example shows that with $p$ conditional statements, the union-of-convex-polyhedra representation requires $\Omega\left(2^{p}\right)$ polyhedra!

* Infeasible to even write down for polyhedral optimizers even when $p=20$
*Polly is LLVM's polyhedral optimizer
*A typical execution of Polly involves
* Representing programs via polyhedral model
* Performing several set operations
*Solving IntLPs


## Integer Set Library (ISL)

*Polly uses Integer Set Library (ISL) to handle polyhedral computations
*ISL uses union-of-convex-polyhedral representation

Problem: Polly terminates without program-optimizations when programs have conditional-structure similar to that of motivating example.

Question: Is there an alternative representation that avoids this blowup? YES!

## Our Results

\& Polyhedral Binary Decision Diagrams (PBDDs) as an alternative representation for non-convex vector sets.
*Proof of concept implementation (Python)

* Case studies comparing scaling behavior of common set operations (needed by Polly) for PBDDs vs ISL's union-of convex-polyhedra representation


## Our Results - Remarks

*Polyhedral Binary Decision Diagrams (PBDDs) as an alternative representation for non-convex polyhedral

* We introduce PBDDs to make representing and performing set operations on nonconvex sets feasible
* Motivating example has a linear size PBDD representation
* Several set-operations become computationally/algorithmically simple
* Particularly useful when these operations result in simple sets, but Polly currently terminates prematurely due to representational overhead.
* Open Question: Adapt PBDDs to work with IntLP solvers.


## Binary Decision Diagrams (BDDs)

*Binary decision diagrams (BDDs) are used to represent Boolean functions

| $x_{1}$ | $x_{2}$ | $x_{3}$ | $f\left(x_{1}, x_{2}, x_{3}\right)$ |
| :--- | :--- | :--- | :--- |
| 0 | 0 | 0 | 1 |
| 0 | 0 | 1 | 1 |
| 0 | 1 | 0 | 0 |
| 0 | 1 | 1 | 0 |
| 1 | 0 | 0 | 0 |
| 1 | 0 | 1 | 1 |
| 1 | 1 | 0 | 1 |
| 1 | 1 | 1 | 0 |



Binary Decision Tree


Binary Decision Diagram

Truth Table
Function Evaluation Examples:

$$
\begin{aligned}
& f(0,1,0)=0 \\
& f(1,1,0)=1
\end{aligned}
$$

## Polyhedral Binary Decision Diagrams (PBDDs)

* In PBDDs, we consider the Boolean function being evaluated as the indicator of whether a point is in the polyhedral set.
- Variables correspond to constraints
*Point in iteration space corresponds to indicator vector of which constraints the point satisfies
* Function evaluation is same as in the case of BDDs


## Polyhedral Binary Decision Diagrams (PBDDs)

Program (recall)

```
for (int i = 1; i <= 6; ++i)
    for (int j = 1; j <= 5; ++j)
        if (i != 3 || j!= 3)
            Stmt(i,j);
```

Statement Domain (recall)


PBDD Representation


Example Evaluations:

$$
\begin{aligned}
& (0,1) \rightarrow F \\
& (2,4) \rightarrow T \\
& (3,3) \rightarrow F
\end{aligned}
$$

## Distinctions from BDDs and QuASTs

*PBDD vs BDD

* An assumption of BDDs is that all the input variables are independent
* For PBDDs that have not been simplified, conflicting constraints can happen
* We allow non-simplified PBDDs as simplification steps often computationally intensive


## *PBDD vs QuAST

* Quasi-Affine Solution Tree
* Used to describe the piece-wise defined solution of the lexicographic minimum of a parametric Z-polyhedron.
* In contrast to PBDD, it is defined by a context-free grammar.
*QuASTs are always trees instead of DAGs.
* QuAST is vector-valued whereas PBDD is Boolean-valued (indicator function).


## Simple Set Operations



## Simple Set Operations

Main paper also defines and gives algorithms for various set operations: *Emptiness check
*Subset check
*Subtraction
*Project Out
*Recursion + Memoization

Note: Algorithms are recursive as our Python PoC implementation of a PBDD is inherently recursive.

## Simplification Operations

We use structural simplifications in order to control the sizes of PBDDs

* Conceptually simple but lead to big speedups

Correctness follows from Shannon Expansion (see main paper)

* Experiments show that these are necessary to make representations tractable.



## Experiments I

(1) Input: $k$, constraints $c_{i}$
(2) $P:=$ Universe
(1) Input: $k$, constraints $c_{i}$
(2) $P:=$ Universe
(3) for $i=1 \ldots k$ :
(a) $P=\operatorname{subtract}\left(P\right.$, intersect $\left.\left(c_{i}, P\right)\right)$
(4) Output $P$



## Experiments II


(a) Non-convex Intersection

(b) Non-convex Union

(c) Non-convex Complement

(d) Non-convex Subtraction

## Experiments III


(a) Non-convex project-out

(b) Non-convex emptiness check

## Future Work

* Implementation that does not rely on ISL intermediate data representation
* Parallelism
*Operational Efficiency
* Simplifications
* Decision Orderings


## See main paper for discussions on each!

* Approximations
*Typed Roots
* Adapt PBDDs for ILP solvers

